Homecare Robotic Systems for Healthcare 4.0: Visions and Enabling Technologies

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***Abstract*—Powered by the technologies that have originated from manufacturing, the fourth revolution of healthcare technologies is happening (Healthcare 4.0). As an example of such revolution, new generation homecare robotic systems (HRS) based on the cyber-physical systems (CPS) with higher speed and more intelligent execution are emerging. In this article, the new visions and features of the CPS-based HRS are proposed. The latest progress in related enabling technologies is reviewed, including artificial intelligence, sensing fundamentals, materials and machines, cloud computing and communication, as well as motion capture and mapping. Finally, the future perspectives of the CPS-based HRS and the technical challenges faced in each technical area are discussed.**

***Index Terms*—Healthcare 4.0, cyber-physical systems, homecare, robotics, early diseases prevention, elderly healthcare, artificial intelligence, cloud computing, flexible sensing.**

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I. Introduction

With the increase of the aging population, the demand for home care services is escalating and pulling the transformation that traditional home care is evolving from open-loop human-dominated systems to closed-loop Homecare Robotic Systems (HRS). However, it can be expected that significant challenges are being faced in this emerging interdisciplinary field, which can be addressed by the enabling technologies originated from Industry 4.0. On the analogy of Industry 4.0, Healthcare 4.0 is used to depict the gradual emergence of the fact that an increasing number of technologies, especially Cyber-Physical Systems (CPS), incubated in the manufacturing sector are being adopted in healthcare [1]. In the context of this new revolution, increasing quantities of CPS are shaping digital healthcare systems involving products, technologies, services, and enterprises [2]. The fundamental components of these CPS arise from a mix of enabling technologies and approaches, including intelligent sensing and actuation, automatic control, autonomous robotics, Internet of Things (IoT), Big Data analytics, Fog and Cloud Computing, and Artificial Intelligence (AI). Challenges faced by today's aging society facilitate the CPS to be applied in Homecare Robotic Systems with higher speed and more intelligent execution, which is an appealing option to provide effective in-home care.

The goal of this article is threefold: 1) to give an overview of homecare robotic systems revolutionized by the Healthcare 4.0; 2) to review the latest research advancement in related topics; and 3) to forecast the directions and challenges for future research. The application scenarios cover one of the emerging research fields in health engineering – homecare – to cope with the effective provision of healthcare services, especially in aging societies. This article focuses on interdisciplinary researches, possible solutions, and pioneering initiatives, crossing AI, sensing fundamentals, new materials and machines, cloud computing and communication, as well as motion capture and mapping.

II. The New Vision and Methodology

A. Core Ideas of the Healthcare 4.0

1) Definition: Given the sustainability challenges around current medical models in developed countries, and the direction

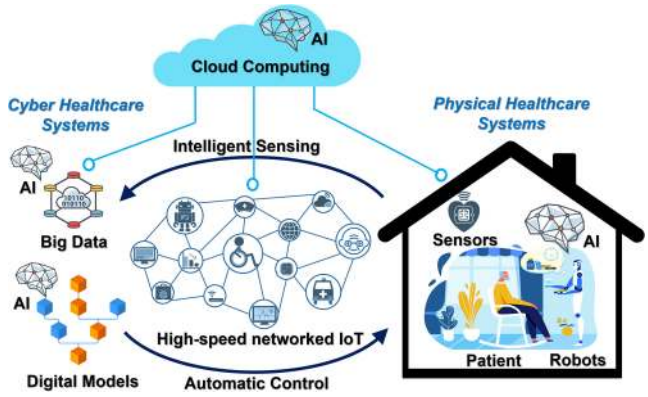

Fig. 1. Illustration of the relationships of new technologies within large-scale AI-powered integrated CPS in Healthcare 4.0.

that healthcare industries and services must evolve to meet these challenges, a clear definition of Healthcare 4.0 is given by:

Healthcare 4.0 is a continuous but disruptive process of transformation of the entire healthcare value chain ranging from medicine and medical equipment production, hospital care, out-of-hospital care, healthcare logistics, and healthy living environment, to financial and social systems. As shown in the Fig. 1, in Healthcare 4.0, vast amount of healthcare devices including sensors and actuators (e.g., healthcare robots) and services in the physical world, i.e., the Physical Healthcare Systems (PHS), are precisely modeled by vast amount of digital models and automation processes in the cyber world, i.e., the Cyber Healthcare Systems (CHS). The Big Data from the PHS to the CHS and the feedback control from the CHS to the PHS are transmitted through high performance IoT networks in real-time, and all the software components are deployed over Cloud and Fog Computing platforms in a fully distributed fashion. Both the PHS and CHS are powered by AI for not only data analytics but all decision making and execution so that manual intervention is minimized. As a result, the Healthcare 4.0 will create not only digitalized healthcare products and technologies but also digitalized healthcare services and enterprises [1].

2) Shift of Design Paradigm: The design paradigm of the healthcare system has fundamentally shifted from open loop to closed loop, from small loop to large loop, and from single loop to multiple loops [3]–[5]. In the past years of development of smart home for home care, considerable single-point devices and systems have been developed. These devices and systems can provide the function of data collection and analytics for home environment monitoring, daily activity tracking, health status assessments, remote control of appliances [1]. In general, there is a lack of automation in terms of decision-making and execution that are currently human-dominated, which is called "open loop". The new paradigms are arising in healthcare to mark an epochal change in the domain, that is, more and more AI-powered high-speed networked healthcare devices are taking over humans in terms of the role for decision-making and execution, which is called "closed loop".

The shift of the Healthcare 4.0's design paradigm occurs at three different levels, i.e., sensing, data fusion, and data interpretation. With single-point devices and systems withdrawing from the healthcare industries, a variety of interoperable smart devices are used to collect data on human health and condition of infrastructure [6]. Computing and processing techniques such as big data analytics and AI are leveraged to fuse, analyze, and manage data [7]. In terms of closing the loop, smart sensing and processing techniques are being combined with actuators and being seamlessly integrated into overall control systems [8]. As a result, the closed-loop, automatic and intelligent executions for instant short-term supports and more professional care services are emerging, such as robot-assisted fall prevention and waking sleep apnea, robotic first aid and tele-medicine. Indeed, the intelligent execution of all kinds of actuators makes it increasingly possible to build the healthcare value chain.

The shift of design paradigm allows for both formal and informal caregivers, more digital healthcare services, and wider enterprises or institutes to be created and to participate in Healthcare 4.0, which aims to realize ultimate vision of the 8-P Healthcare: preventive, predictive, participatory, patient-centered, personalized, precision, pre-emptive, and pervasive healthcare [1], [9].

B. The New Vision of CPS-Based Homecare Robotic Systems

As shown in Fig. 2, the CPS-based homecare robotic system (CPS-HRS) is experiencing a design paradigm shift from the open, small, single loops to the closed, large, multiple loops more reflective of holistic care, where humans and robots share their capabilities and intelligence. A typical cyber-physical coupling system consists of three parts: cyber part, physical part, and cyber-physical interaction modules [10]. These three parts are closely connected via those loops. The cyber part includes sensing, actuating, computing, and communication hardware/software. The physical part consists of care recipients, doctors, family members, and robots. The cyber-physical interaction modules are composed of data processing, analysis, and transmission modules, interfacing modules, and control modules. The ultimate purpose of using cyber infrastructure is to intelligently and automatically monitor (from physical to cyber) and control (from cyber to physical) the physical homecare robotic system via interaction modules, realizing the closed loops of the revolution mentioned above. The goal of the CPS-HRS is to establish a new system to support computational and cognitive homecare services based on robotics.

C. New Services Enabled by the CPS-HRS

The proposed design has the intrinsic characteristic of a CPS providing tight coupling of computational parts and physical parts (e.g., patients and robots). It has several cyber–physical interactions via closed feedback loops, as illustrated in Fig. 3.

The elderly usually lack self-care ability limited by their body function [11]. Practical implementations of the robot-assisted living can be enabled based on the CPS-HRS. Various functional devices and robots will be designed based on specific functional requirements. For example, the elderly have difficulty in using bathrooms, which can be assisted by robots to increase the quality of life [12]. The current number of professional rehabilitation trainers does not meet the needs of patients' rehabilitation training. The CPS-HRS provides a solution using

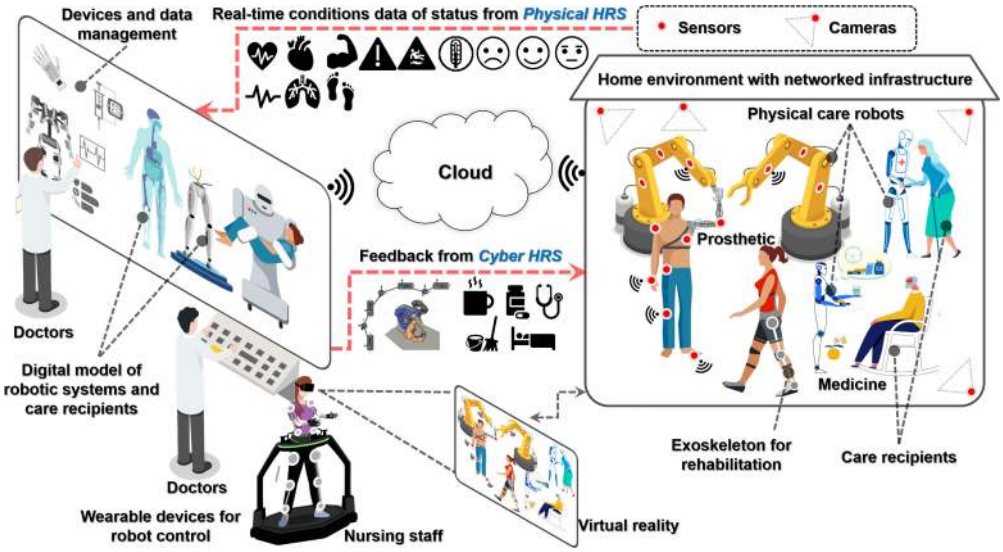

Fig. 2. Illustration of the concept of the CPS-HRS, composing of cyber HRS and physical HRS. The information flow in the CPS-HRS is bidirectional. Devices and data are managed and analyzed respectively according to the real-time conditions data of status transferred from physical HRS to cyber HRS. Robots and devices in physical HRS are connected and controlled by the feedback generated by the digital model of robotic systems and care recipients from cyber HRS.

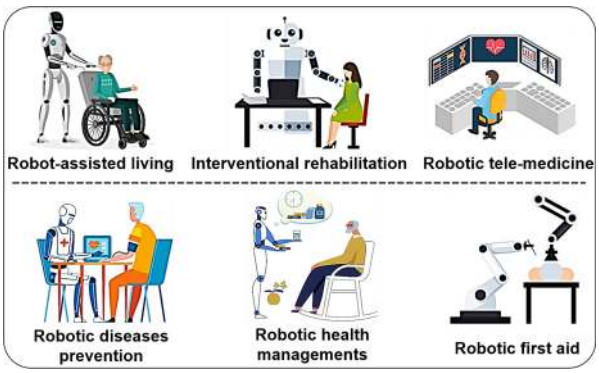

Fig. 3. Illustration of emerging application scenarios enabled by cyber–physical interactions via closed loops in the CPS-HRS. The typical examples of cyber–physical interactions are: infrastructure-robot interaction for robotic daily housework; human-robot interaction for robot-assisted living, first aid, diseases prevention, and health managements; infrastructure-human interaction for interventional rehabilitation; infrastructure-human-robot interaction for robotic tele-medicine.

robotic interventional rehabilitation training [13]. Besides, the monitoring and measurements for patients must be conducted in a hospital under the doctor's or nurse's support. The CPS-HRS provides a novel way of implementing the tele-medicine, in which the doctor or the nurse can conduct some necessary measurements based on special devices [14]. Another important service enabled by the CPS-HRS is the robotic first aid based on the teleoperation technology, such as putting and starting the patch of automatic external defibrillator (AED) on the patient's body, which improve the efficiency and the success rate of first aid [15]. In addition, supported by the development of AI and big data technologies, disease prevention will be a significant application. For instance, early and specific diagnosis is considered important as it can help to guide Alzheimer's disease and dementia therapy, which can be further enhanced based on the CPS-HRS [16]. Besides, cognitive decline is an obvious symptom of dementia patients. Timely and accurate independent medication is difficult for people with dementia. Robotic health managements will be a focus of CPS-HRS with the development of IoT-enabled devices [17]–[19].

D. New Features Enabled by Closed Loop Feedback

1) Affective Human-Robot-Interaction: In the past few decades, human-robot interaction (HRI) has become an increasingly important research area in the cross-disciplinary fields of psychology, behavioral science, and cognitive science. It includes both the development of robots with human involvement and the study of how humans and robots interact [20]. Past HRI researches have focused on how humans control robots. However, for healthcare robots, they need to communicate with the user in order to optimize their performance. Therefore, the robot must be able to effectively recognize, interpret, and respond to the emotions expressed by humans, given such emotions convey important aspects of interaction, namely thoughts and feelings.

Two major models have been identified in the field of neuroscience and cognitive science, describing how people perceive and classify affection: categorical model and dimensional model [21]. Many affective human-robot interaction studies use categorical models for facial expressions [22], body language [23], voice [24], physiological signals [25], and multi-modal systems [26]. The model allows the robot to interpret emotions in a similar way to humans [27]. The most common discrete affective categories that robots use in HRI settings are surprise, anger, disgust, fear, sad, happy, and neutral. These affective categories contain the six basic affection of Ekman and have been used to infer appropriate social robot responses in various HRI scenarios [28]. In the near future, healthcare robots will inhabit human

environments. These communication skills are one of the keys to the human acceptance of healthcare robots.

2) Seamless Infrastructure-Robot-Interaction: A large number of single point smart devices and open-loop systems have been developed with the expansion of IoT and smart infrastructures [29]. Enabled by closed-loop feedback, we believe that the CPS-HRS will integrate all the smart devices in the home environment to promote and advance seamless infrastructure-robot-interaction. More abundant and detailed data about the condition of infrastructure and the information of the surrounding environments that impact on human health can be collected [30]. Therefore, more optimized decision results for special cases can be made based on computing [31] and AI [32]. The CPS-HRS in the future eventually closes the loop by intelligent execution through all kinds of actuators based on the decisions made. Based on the obtained fusion information, the CPS-HRS can make a more suitable decision to sequential problems and perform accountable actions in homecare cases [33].

3) Human-Robot-Symbiosis: A variety of advanced robots have entered human workspaces or living spaces with rapid advances in robotic technology [34]. These robots can operate side by side with humans or assist humans with specific tasks without the need for physical barriers, i.e., fences [35]. In this case, how to ensure security and realize human-robot-symbiosis will be an emerging research topic [36]. Social robots and assistive robots will be two practical hot topics in this field.

In the above context, the next generation of robot companions or robot working partners will take the initiative to ensure interaction security. Advanced sensing technology, such as flexible robot skin tactile sensor, and joint moment sensor, guarantees the security of interaction [37], [38]. Combining with the deep learning or other AI solutions and motion capture technology, the HRS will be able to accurately sense and identify people's behavior, so as to predict collision [39], actively avoid obstacles, or perform other actions, in order to ensure the security of human-robot-symbiosis.

4) Teleoperation of Collaborative Robots: With the aging population, the lack of home caregivers will be a big problem [11]. Teleoperation is a promising solution for this problem, which uses robotic devices remotely according to the operator's intention [30]. For the relatively easy assistive operations, the robot can accomplish those operations autonomously. For the half-disabled elderly which are partially incapacitated, they can teleoperate the robot using their remaining capabilities to support independent living. Besides, teleoperation can realize the on-site professional operation of the people who have professional skills, such as the caregivers who work in the healthcare institutions can teleoperate the robot to care these elderly in home. Collaborative robot, a.k.a. "Cobot", is an example of the current development phase of human-robot-symbiosis. It permits a safe interaction between robots and humans working for the same or interrelated processes. The combination of teleoperation and cobot for homecare will be a major trend of CPS-HRS. In this trend, some new use cases will emerge for making up for the lack of caregivers and reducing the cost of homecare.

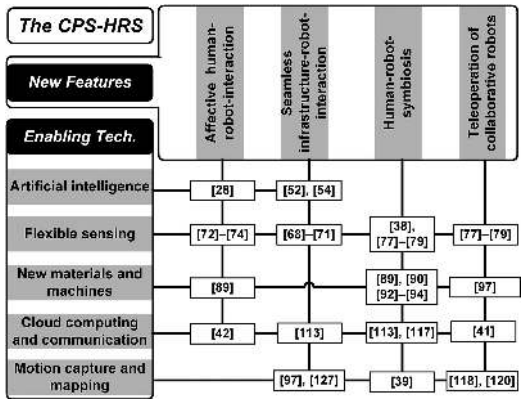

Fig. 4. Illustration of four new features enabled by five technologies with supplementary reference, clearly providing the relationships between features and technologies. Given by this reference map, the individual importance of these technologies for constructing the CPS-HRS can be initially concluded.

The integration of advanced sensing, AI, new materials and machines ensure the security interaction ability of cobot [31]. This makes it possible for cobot to provide care in the new vision of HRS. Advanced motion capture technologies and novel motion mapping methods will provide a more natural and effective way of capturing the operator's intention for teleoperation [40]. In the future, the CPS-HRS will involve the caregiver or other professional personnel in the hospital as the remote tele-operator.

E. Enabling Technologies

The distinguishing features mentioned above are enabled by technologies that have originated from the manufacturing industry, such as flexible sensing, new materials and machines, cloud computing and communication, AI, and motion capture and mapping. AI empowers the CPS-HRS with the capability in the analysis of complex health or medical data for prevention or treatment. Flexible sensing provides data support for the analysis of a patient's health condition. New materials and machines expand the application scenarios of the CPS-HRS. Cloud computing and communication are the key technologies to build a connection between the cyber world and the physical world [41], [42]. Motion capture and mapping enable the teleoperation of homecare robots. As shown in Fig. 4, the following sections will cover these five enabling technologies and bridge the gap between enabling technologies and new features in CPS-HRS.

III. Artificial Intelligence for the CPS-HRS

Benefited by the recent progress of AI, wireless communication, cloud computing, and big data technology [7], there are new homecare situations for the elderly, where robots and intelligent technologies are at the core. In the AI-powered CPS-HRS, robots can be used as the second body of expert doctors and professional caregivers, performing disease prediction, assisted diagnosis, assisted therapy, and assisted rehabilitation. The AI for the intelligent hospital can also be applied to the home-based, community-based healthcare of the elderly in the CPS-HRS.

A. Disease Prediction

As analysis mining and integration of data by AI become faster and more accurate, features outside accepted ranges can be identified early and when appropriately combined used to avoid serious consequences or complications. For example, the Moorfields Eye Hospital in the UK has developed a machine learning system with Google DeepMind to perform early screening for two major diseases causing vision loss: diabetic retinopathy and age-related macular degeneration. Google claims that the application of the mobile platform will save 10,000 patients from vision loss every year [43]. Chen *et al.* [44] proposed a new convolutional neural network based multimodal disease risk prediction (CNN-MDRP) algorithm using structured and unstructured real data from the hospital and an experiment on the prediction of a regional chronic disease of cerebral infarction. The accuracy reaches 94.8%. The accurate analysis of medical data benefits early disease detection, patient care and community services.

B. Intelligent Hospital

Due to the shortage of healthcare resources, a common trend is that the hospitalization experience of patients is poor. To alleviate this pressure, many countries have started to implement the AI approaches with medical treatment: Thomas Jefferson University Hospital launched an intelligent hospital supported by the IBM Watson IoT in 2016. Through IBM's cognitive computing and natural language processor, the patient can customize the ward environment according to his or her needs, and obtain the information by dialoguing with the system. The platform assists healthcare staff interacting with patients and recording and storing conversations for later healthcare examinations. Telemedicine and remote consultation and diagnosis can also be achieved using high-speed wireless communication technology [45]. Alder Hey children's hospital in Liverpool, United Kingdom, in collaboration with the Science and Technology Facilities Council's (STFC) Hartree Centre created the United Kingdom's first 'cognitive' hospital by harnessing 'big data' and the power of IBM's Watson technology platform. Alder Hey will greatly enhance patient experience by identifying patient anxieties and providing information and reassurance on-demand; reminding young patients and their parents about appointments and aftercare; and providing insightful feedback to clinicians based on the tone and sentiment of these interactions. It can provide more personalized service for a child and make significant cost savings [46].

C. Assisted Diagnosis

In recent years, the development of image processing technology and deep learning technology have continued to develop, so that in medical diagnosis, Computer-Aided Detection/Diagnosis (CAD/CADx) can help pathologists make more objective and effective judgments. Das *et al.* [47] developed a machine learning framework based on the alternating decision (AD) tree technique and three neural network models, including probabilistic, radial basis function, and multilayer perceptron neural networks. The AD tree simulates human brain cognition to analyze complex medical data and automatically interpret lung function tests and computed tomography results to diagnose the most common obstructive pulmonary diseases. Medical image assisted diagnosis technology based on deep neural networks has also been wildly studied and get high accuracy in the classification of Parkinson's disease [48], lung cancer [49], breast cancer [50], and diabetic retinopathy [51].

D. Assisted Therapy

The development of four sub-areas of AI (deep learning, artificial neural network, natural language processing, and computer vision) enhances treatment efficiency and quality, mainly reflected in big data analysis, building intelligent shared databases, and providing favorable clinical decision support [52]. In the future, doctors will be able to use intelligent analysis to derive specific data on each stage of patient treatment: Before treatment, the patient will be automatically monitored to extract such parameters as body weight, blood sugar, nutrition, activities, and using mobile applications and wearable sensors with upload to an electronic health records (EHR) [53]. Automated analysis of clinical data prior to treatment provides a doctor with a more specific assessment of treatment risk. During treatment, by integrating the real-time data of the treatment process the doctor can make more accurate clinical decisions during the treatment process according to the analysis results, and reduce or avoid the occurrence of adverse events [54].

E. Assisted Rehabilitation

After treatment, smart devices perform an integrated analysis of all data (before, during, and after treatment) to help patients understand recovery status and effectively predict complications. After discharge, wearable healthcare devices will continue to record the patient's vital signs data, and integrate it with the data since the patient was admitted to the hospital to truly achieve patient-centered care [54].

The involvement of AI and the Internet of Healthcare Things (IoHT) will promote the entire process of medical treatment [55]. The usage of IoHT will get more accurate and comprehensive medical data, and AI will reduce human workload as well as decrease the workforce needed for the caring process (e.g., doctors, medical equipment technicians, and allied health workers) [56].

IV. Flexible Sensing for the CPS-HRS

Flexible sensing is emerging as a significant technology to enable the invention and fabrication of sensors, using flexible materials. Compared with conventional sensors based on rigid materials, flexible sensors have excellent properties, such as high bendability, stretchability and ultrasensitivity [57]. Thus, they could be conformally attached to an arbitrary surface, such as human skin and robot contours, for health monitoring. In addition, flexible sensors can also be applied to environmental cognition and robot perception to provide a safer and more comfortable human-robot interface in the CPS-HRS.

A. Flexible Sensing for Human Health Monitoring

The advancement of flexible sensing technologies facilitates the development of wearable devices. It can be foreseen that wearable devices will be wildly applied in the future, as they endow chronic disease care systems with the capability of remote and real-time monitoring of biomedical signals along with other symptoms, including actimetry and mobility [58].

The ECG is a direct indicator of heart electrical activity with important clinical significance. Wearable devices, such as electronic tattoo, can be directly attached to human skin for long-term measurement of ECG [59]. These devices provide the possibility of a novel clinical method of BP monitoring by softly laminating on the skin. In the future, pressure transients of arterial blood flow and heart rate variability could be continuous and non-invasive monitored in real time [60], [61]. Body temperature is a vital index of human health, which is also closely related to various types of ailments such as sepsis, inflammatory disease, infection, and heatstroke [58]. To satisfy the requirements of wearability, the temperature sensors need to be portable, flexible, and conformal to human skin [62]. Wearable devices have also been applied for plantar pressure detection [63]. By attaching pressure sensors to insoles or shoes, the plantar pressure distribution can be extracted for gait analysis [64]. In addition, activities of daily living could also be monitored by flexible sensors embedded into the ambient environment or as smart objects interacting with subjects, such as steering wheel [65], pillow-case [66], or toothbrush [67].

B. Flexible Sensing for Environmental Cognition

Environmental parameters such as humidity, gas concentration, and light illumination are essential components in HRS, which can also be monitored continuously and precisely by advanced flexible sensors, so that human beings could be protected from the deleterious environment. As to humidity sensing, various flexible sensors based on different mechanisms have been studied. The common feature of humidity sensors is that the change of humidity can lead to a variety of electrical parameters [68]. With the increasing problems of environmental pollution, it is of great value to detect gas concentration in surroundings. Flexible gas sensors could be attached to arbitrary surfaces such as a wall, furniture, some portable devices, or even human skin [69], [70]. For light illumination, a variety of flexible sensors have also been reported based on the mechanism that light illumination can stimulate electrons to produce photocurrent [71].

C. Flexible Sensing for Robot Perception

The assistant robot is the main service provider in HRS. During social interaction, the detection of tactile stimuli is one of the primary methods that human extract information from their surroundings. It is similar for robots when they work or interact with humans in HRS. Flexible sensors attached to robot surfaces, which can also be called robot skin, endow a robot with the capability of tactile perception. Pressure is one of the most common signals in HRI. There has been a great number of research publications on pressure or strain sensors for robot skin [72], [73]. Notably, to better imitate the capabilities of human skin, increasing the variety of perception functions with different kinds of sensors is an important research direction of robot skin. At present, a commonly used method to fabricate flexible temperature sensors for robot skin is to fix the temperature-sensitive material to a flexible substrate [74].

D. Flexible Sensing for Human-Robot Interface

To achieve more substantive functionality for disadvantaged groups, assistant robots, Hobbit and Care-O-bot for instance, are increasingly being used to homecare field [75], [76]. Thus, human physiological signals, such as electroencephalogram signals [77], gestures [78], and joint motions [79], could be collected by sensors to achieve real-time robot teleoperation control, providing service for the disabled. However, assistant robots with rigid surfaces are very likely to do harm to humans. To ensure safety in HRI, efforts have been made in developing various types of soft robotic skins to minimize the damage in the case of collision [38].

V. New Materials and Machines for the CPS-HRS

A. New Materials for Sensors

For more precise monitoring of biomedical parameters, sensors are normally placed in contact with the human body. Thus, comfort and safety are critical factors to be considered during sensors design. With the advances of nanoscience and nanotechnology, sensors applied to human body are typically fabricated to be flexible, which is mainly composed of a flexible substrate and conductive fillers. To date, commonly adopted materials of substrate include polydimethylsiloxane (PDMS) [80], polyimide (PI) [81] and polyethylene terephthalate (PET) [82]. To convert biomedical signals into processable electrical signals, conductive fillers are deposited in the substrate, electrical properties of which can be significantly changed under external stimuli. Presently, various materials have been used as conductive fillers, such as metallic nanowires [83], carbon nanotubes [84] and reduced graphene oxide [85]. In the scenarios of neural activity sensing, electrodes are required for stimuli and sensory feedback. Traditional electrodes made of rigid materials cannot provide long-term and robust interfaces with neurons, neural fascicles, and nerves. Currently, new materials have been applied to electrode fabrication by inserting platinum wires into flexible substrate [86], [87].

B. New Materials for Robots

Social robots and assistive robots are significant components in the CPS-HRS, given they can take on homecare tasks for older or disabled people. Conventional robots are mainly made of rigid materials, such as steel and iron, which can lead to a feeling of distance and compromising safety during HRI [88]. With the advancement of new materials, various types of artificial skins are designed to endow robots with multimodal perception. To be concrete, by covering robot surface with flexible conductive polymer or utilizing material spraying technique to directly

form a uniform piezoelectric film on a robot, external tactile stimuli can be converted to electrical signals for perception [37]. Meanwhile, it is a critical mission to improve the safety levels of the CPS-HRS. Thus, soft materials could be adopted to create a safer human-robot interface in case of an immediate collision with humans [89]. Moreover, new materials can also be applied to construct the main body of a robot to enable safe interaction [90].

C. New Machines

There have been various studies on new devices, which can be applied for human power augmentation, motion assist, or rehabilitation. The exoskeleton robot is one of the major research directions for minimizing workload so that human efforts can be reduced. On one hand, exoskeleton robot can be applied to the upper limbs of human beings to perform task-oriented repetitive movements, in order to improve muscle function that was decreased by diseases like stroke [91]. On the other hand, it can also provide a device-based approach to safely and effectively improving the walking state of disabled groups [92]. Although the athletic ability of the human wearer is enhanced by the exoskeleton robot, the total weight also increased. Hence, research has been carried out for devices with lower weight and better power consumption, such as robotic suits or soft actuators for joint support [93], [94]. While machines mentioned above mainly aim to assist patients with complete limbs, related studies are targeting amputees who lose motility due to injury or disease. Prosthetics are such devices designed to restore physiological functions of the disabled, researches of which mainly focus on upper limb prosthetics [95], and lower limb prosthetics [96]. Furthermore, with the convergence of the fields of robotics, automation, embedded system, and AI, traditional manual powered equipment, a wheelchair for instance, has also been replaced and created to support the disabled community [97].

In addition, control algorithms are important to achieve better performance of new machines in the CPS-HRS. On one hand, classification algorithms, support vector machine for example [98], are leveraged to recognize body signals, such as electromyography (EMG), thus tracking human motion intention and realize follower motion assistance. On the other hand, adaptive algorithms [99] and neural network algorithms [100] are adopted to optimize the dynamic relationship between the position deviation of the joint and the force acting on it, thereby ensuring precise pose control.

D. New Human-Robot Interfaces

To date, various human-robot interfaces have been proposed to achieve signal transmission between human body and new machines. Neuroprosthetics are such interfaces to facilitate motor, sensory, or cognitive-communication between the nervous system and a prosthetic device by leveraging spared brain and spinal circuits, thus restoring physiological functions [101]. Generally, electrodes are placed near the tissues or cells in a specific region. For one thing, they could be localized to the Central Nervous System (CNS), such as the brain or spinal cord, serving as Brain-Computer Interface (BCI) [102]. For another, electrodes could also be located to a nervous system outside the CNS, a peripheral nervous system for instance, to transmit command signals to the prosthetics [103]. As to BCIs, the three major signal acquisition methods are electroencephalography (EEG) [104], electrocorticography (ECoG) [105], and intracortical electrodes [106], invasiveness and signal resolution increasing simultaneously in turn. On one hand, the immune response caused by noninvasive BCIs is less, while the output capabilities of which are limited by their resolution. On the other hand, invasive BCIs like intracortical electrodes can lead to rejection of the users, due to the risk of the implantation operation. In addition, deep brain stimulation (DBS) technology, an effective surgical procedure for the treatment of a spectrum of neurological disorders such as Parkinson's disease and essential tremor, could act as BCI for specific patients as well [107].

Considering the weak signal intensity of nerves, human-robot interface based on EMG is also proposed for exoskeleton robots or prosthetics control [108], [109]. By attaching electrodes to the skin, electrical signals of selected muscles could be obtained, which have an amplitude several orders of magnitude larger than those of nerves. Several other interfaces have also been presented that extract signals from parallel systems such as the eyes [110], the voice [111], or the head [112] to derive the user's motion intention.

VI. Cloud Computing and Communication for the CPS-HRS

A. Cloud Computing

Cloud computing is a large-scale distributed computing architecture in which users can lease computing resources for storing, processing, and managing data in real time. There are normally three types of service models offered by cloud computing: Infrastructure as a Service (IaaS), Platform as a Service (PaaS), and Software as a Service (SaaS). For instance, the CloudThink facilitates shared path learning, including traffic routing in Fig. 5(a) [113]. The main advantages of cloud computing are [114]: 1) a virtualized platform for easy and efficient interaction with other agents and external servers; 2) handling the massive storage and processing of data in the cloud; 3) flexible configuration, high scalability, and expanded capacity; and 4) simplifying the maintenance and updating of software and drivers.

These advantages promote popularity among other research fields, such as robotics. Robots connected to the cloud can offload complex computational, storage, and communication work to the cloud, and share information from various agents, which endows robots with the characteristics of the service model, Robot as a Service (RaaS). The applications of RaaS combining the robot with cloud computing in terms of accessing robots and controlling robots are detailed herein.

Accessing robots: Cloud computing takes advantage of scalable computing resources to facilitate accessing CPS-HRS in the RaaS. A platform based on cloud computing provides access to the data of robots in the cloud for users. For example, Parallel Cloud Computing has been used to acquire the results from the cross-product of perturbations in object and environment and

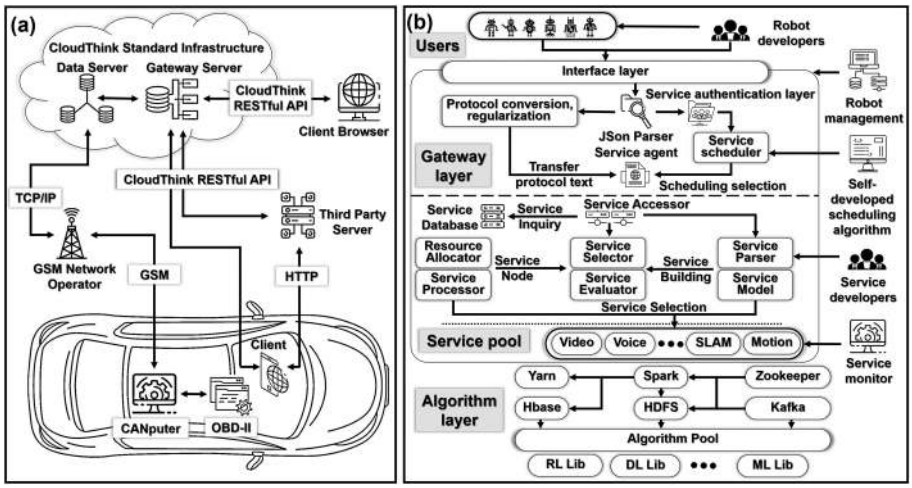

Fig. 5. The architecture of applications based on the cloud computing. (a) The architecture of CloudThink for traffic routing and other applications [113]. (b) The architecture of the service robot cloud platform [116].

robot response to sensors and commands [115]. In addition, it is also useful to speed up motion planning methods in CPS-HRS, such as realizing Simultaneous Localization and Mapping (SLAM) in the Cloud [116]. In Fig. 5(b), the architecture of a new service robot cloud platform is presented [116]. It should be noted that the integration of cloud computing and robotics extends the accessibility of CPS-HRS.

Controlling robots: Related data and information generated by CPS-HRS are stored in the cloud. The physical robot shares the data with other agents through RaaS and provides services. Considering various applications of CPS-HRS, it should be applied under different scenarios such as cooperating with humans or replacing humans to execute routine tasks. Acquiring the requests committed by robotic applications and scheduling the corresponding commands to the robot are the critical procedures of robotic applications in the cloud. In [117], the robot cloud panels based on the Google App Engine and RaaS extension received the users' requests and stored and processed data using Cloud Computing.

With the development of cloud computing, not only the applications of robotics, but also the IoHT is promoted. IoHT collects data from numerous devices based on cloud computing, which makes HRI more interconnected and intelligent [118].

B. Communication

Increasingly developed communication technologies form the backbone of Healthcare 4.0 allows the interaction and dissemination of data and information related to the HRS, alleviating limitation of distance and remoteness [119]. Previous generations of mobile communication systems have already evolved with the impacts of extending the network capabilities and enhancing the user experience. 5G is the fifth generation of cellular network technology, which consists of three main uses: Enhanced Mobile Broadband (eMBB), Ultra Reliable Low Latency Communications (URLLC), and Massive Machine Type Communications (mMTC). On the road towards the common vision of Healthcare 4.0, 5G triggers the development of potential products and services by the combination of networking, computing, and storage resources. CPS-HRS is expected to remove distance and time barriers to tele-healthcare provisions, such as teleoperated surgical systems benefiting from the introduction of 5G. In addition, 5G will replace cables, reduce costs, and thus enable wider adoption and utilization of the robotic service platforms globally [120].

Communication is a steppingstone on the way to fulfill the vision of CPS-HRS. In addition, the enhancement of computing technology is the main enabler of CPS-HRS by increasing the accessibility, exchange, and sharing of the related data.

C. Security and Privacy

With the development of IoT technology, numerous personal healthcare data are generated; therefore, security and privacy are major issues of healthcare information [121]. Block chain is a decentralized core architecture, which has become the focus of security research in recent years [122].

With the integration of technologies, the block chain adopts distributed accounting, distributed communication and distributed storage. Block chain consists of many equal nodes to form an end-to-end network. The data exchanged between nodes can be verified in the premise of obeying the established rules. The block chain utilizes the consensus agreement of nodes to handle with the additions of blocks to ensure the security and privacy of information. Massachusetts Institute of Technology (MIT) with its project called Medrec, has shared healthcare data between electronic health records (EHRs) via block chain [123]. By contrast, the first EHR on the basis of holding the ownership of the protected health information (PHI) by patients, has been developed by the Initial Coin Offering (ICO) for Medical Chain [124]. Within the security and privacy system, all parties are allowed to use the data with the presentation of authentication. Different limits of authority are given by different use identities, such as viewing privileges of the block chain are provided to only authorized users.

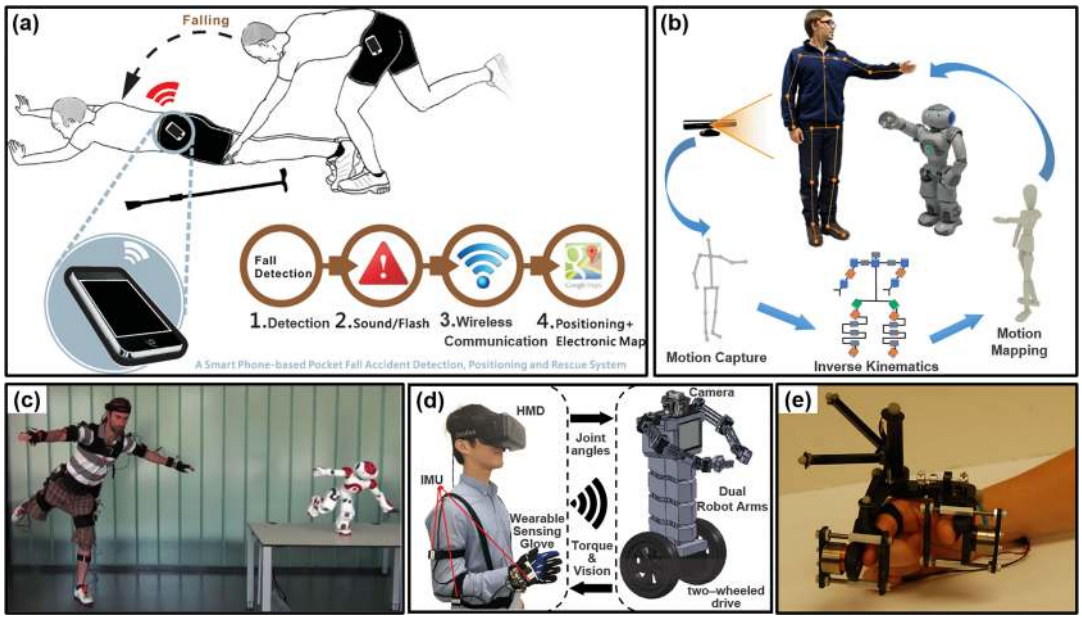

Fig. 6. Motion capture and mapping for the CPS-HRS. (a) A smart phone-based pocket fall accident detection, positioning, and rescue system [130]. (b) Illustration of teleoperating humanoid robot NAO using Kinect depth camera [133]. (c) Nao imitating complex whole-body motions using the Xsense MVN motion capture system [131]. (d) A tele-operation Interface with a motion capture system [137]. (e) The wearable haptic device controlled the opening of the robot's gripper [139].

VII. Motion Capture and Mapping for the CPS-HRS

A. Motion Capture for Behavior Analytics

Human behavior analytics of the elderly or other caretakers at home is an important component of CPS-HRS. Motion capture is an effective way to permit behavior monitoring of older people in a more natural setting [125]. Advances in sensor technology over recent years have provided new ways to monitor the elderly in uncontrolled home environments [126]. Vision-based sensors and wearable sensors are two main methods of motion capture [127]. Sensors have become smaller, cheaper, and wearable, which form a body network of sensors to promote the practical application of dynamic action capture homecare. Motion capture in the CPS-HRS can monitor the progression of disease through behavioral analysis [126]. In addition, reliable fall detection, fall prevention, and emergency assistance notification can be achieved based on motion capture [128], [129]. Using a smartphone-based pocket fall accident detector to detect fall is typical, as shown in Fig. 6(a) [130]. These applications improve the quality of life for the elderly.

B. Motion Mapping for Teleoperation

Motion capture is the process of obtaining the operator's motion data, while motion mapping converts the operator's motion to the robot's motion based on the obtained motion data [131]. Humanoid robots with different body morphologies will be a big component in CPS-HRS. Transferring human motion to humanoid robots is a promising way toward intuitive programming [132]. In order to control the robot effectively, the motion capture data need to be converted to the format that can be programmed in the robot's low-level controller. The tool central point (TCP) position-orientation and the joint angles are two common kinds of programmed data for robotic control. Accurate position can be obtained by mapping the position-orientation data of the operator's hand to the TCP of a humanoid robot. Human-like motion can be generated by establishing the mapping relationship between the Denavit-Hartenberg (D-H) model of the humanoid robot and the operator [133]. Fig. 6(b) illustrates the motion mapping progress of teleoperating humanoid robot NAO (SoftBank Robotics Inc. [134]) based on the motion data obtained from Kinect (Microsoft Inc. [135]). In addition, considering the whole-body motion of humanoid robots, to realize the basic kinematic motion mapping, the related dynamic factors should also be considered to ensure the stability of humanoid robots in the process of walking [131]. Fig. 6(c) shows the whole-body teleoperation system that enables a NAO to imitate complex whole-body motions of humans in real time.

C. Real Time Motion Capture for Teleoperation

As described in the new features of CPS-HRS, teleoperation technology will be an important part of the practical application of homecare. As a method for remotely controlling a robot interacting with uncertain environments, teleoperation is a human-in-the-loop architecture [136]. The homecare robot is still hard to program, although examples of advanced program methods, such as drag-and-drop applications, are emerging [131]. It would be useful if the robot could learn human skills and utilize the human's environment adaptation ability. A promising method is that the robot can follow human motion in real time. To achieve this goal, human motion needs to be captured in real time [137]. Extra vision-based sensors and fixed sensors on the human body are the two most commonly used methods for real time human

motion capture [138]. Visual-based motion capture systems are relatively straightforward but rely on a controlled setting with multiple fixed sensors. Wearable fixed sensors tend to be costly and inconvenient and will limit actual operation [133]. In order to control the grippers or other end effectors of a robot, some devices for capturing the motion data of human hands, such as the data gloves shown in Fig. 6(d) and the exoskeleton shown in Fig 6(e) have been developed [139]. In the future with the development and adoption of edge computing, motion capture technology will intuitively capture the intentions of the operators without additional training costs. Teleoperation technology based on motion capture will bring more novel applications to remote homecare.

VIII. Future Directions and Challenges

A. Artificial Intelligence and Homecare Robotic Systems

We now have powerful computational resources, large processing and storage capabilities and increasingly sophisticated algorithms and analytical techniques to mine relevant medical information from the big data associated with healthcare. Collectively, this big healthcare data (BHD) and AI techniques can be used to effectively reduce the burden of medical systems and healthcare costs. Further, the combination of BHD and AI can be used for early detection, diagnosis, treatment, and even prediction of health and wellness problems, especially for the rising older population. In addition, BHD and AI when combined with HRS can perform a variety of tasks currently done by healthcare professionals so that these professionals can focus on interacting with patients to provide more efficient and high quality care [140]. Corresponding examples include taking care of the nutritional needs of patients, helping them with mobility and exercises that may be part of rehabilitation, especially after surgery, and medical administrative tasks including booking appointments, communicating medical information, processing prescriptions and ensuring medications adherence.

Intelligent automated healthcare robotic systems have the potential to dramatically change various aspects of healthcare. For example, robotic systems with humanoid designs and natural language processing (NLP) capabilities can help the elderly maintain their independence, improve social interactions, reduce loneliness and help with long term chronic conditions. In fact, these robotic systems are expected to replace human caregivers for geriatric patients, provide relevant medical information to health questions, and perform tests such as fast and precise venipuncture for blood analysis [141], [142]. We can also imagine a future where intelligent automated HRS and the IoHT represent a paradigm shift in personalized medicine, including diagnostics, treatment, and rehabilitation. This future will also include the big data from intelligent automated HRS and IoHT which can be used to predict health events even before they occur in patients, thus lowering healthcare costs and improving the health and well-being of patients [143]–[145].

Despite the many attractive features of intelligent automated HRS, there are several challenges that need to be addressed.

1) First, is the problem of security and privacy of healthcare data to address and manage new cybersecurity risks, especially with the increasing use of cloud-based servers and the proliferation of wireless connectivity [143].
2) A second issue is related to identifying bias in healthcare datasets, especially with respect to socioeconomic, educational, ethnic and geographic variations. If such biases are not properly resolved, then it would be difficult to address the differences in care and outcomes across these different groups of the population.
3) A third issue is related to the accuracy and quality of data that needs to be verified before applying in AI models. Thus, we need to verify both the accuracy and consistency of labeled data. For the training data, consistency is required to ensure that labels agree with one another and are accurate. Generally, accuracy is measured by comparing the labeled data to a subset of the training data that has been labeled by data scientists or experts.
4) A fourth issue is related to the intuition of experienced healthcare professionals that are very difficult to capture and store as BHD. Intuition is often developed through experiences, non-analytical reasoning and thinking, feelings, a solid knowledge base and non-linear creation of knowledge. In patient care, intuition is very valuable and is often used because when needed, it re-emerges in the form of "intuitive intelligence" or "gut feelings". However, because intuition is very difficult to capture or quantify, and thus stored so it can be later uncovered or mined as with other BHD; intuitive knowledge is often regarded as non-scientific and not suitable in investigations in the sciences including healthcare. This is in contrast to evidence-based medicine and decision making based on quantitative information from patients' data and improved health outcomes that can be measured and stored as BHD for later use.
5) A fifth issue is related to experienced clinicians being able to identify non-traditional medical signals such as emotional cues, speaking patterns and behavioral signals, and using this information in diagnosis and treatment. Another example of such non-medical cues is related to secondary factors including emotional and alertness state, engagement, skin tone, breathing patterns that are all important when feeding a patient. Presently, it is very difficult for AI-based humanoid robotic healthcare systems to accurately collect, document and use such secondary factors.
6) A sixth issue is related to the bias of the developers of algorithms and the diversity and heterogeneity of big data used to train HRS. This may seem paradoxical because artificial intelligence was proposed as a solution to bias since computers are supposed to be unbiased. However, intelligent, self-learning software could be trained with improper or biased data or with data to give one segment of the population advantages. Therefore, diversity and heterogeneity of big data that is also representative of the population it will be used for, is needed to train the intelligent software for applications such as homecare robotic systems. But even with safeguards for such bias, which can be regarded as conscious bias, safeguarding against

unconscious bias is much more difficult. Some solutions include looking at AI predictions which are counter to reality to ensure that they are not coded with bias. This involves close cooperation among many experts including data scientists, AI researchers and social scientists.

However, despite these challenges, the future prospects for AI-based automated HRS are very bright.

B. Advanced Soft Materials and Bio-Machines

To obtain precise health data in real time and provide necessary and timely assistance to the users in the CPS-HRS, new materials and machines are critical technical foundation. From the perspective of new materials, nanotechnology and polymer technology have been increasingly applied to wearable devices and robot skins to enable better health monitoring and HRI. Existing research directions and challenges mainly focus on improving the properties and performances of nanomaterials. However, the high prices and complicated fabrication process of existing metallic nanomaterials hinder their large-scale application [146]. By contrast, chemical vapor deposition processes for fabrication of carbon-based nanomaterials has been well-established, but the relatively low conductivity and stability of carbon-based nanomaterials to date have limited their applications in homecare services [72]. Polymer materials are also currently adapted to fabricate flexible substrates such as PDMS and PI, both of which have excellent flexibility and stretchability [87], [147]. However, their low adhesion to conductive elements limits the electrical interconnects on their surface. In future research for the CPS-HRS, to achieve better comfort of wearable devices and softer tactility of robot skins, new materials should be further developed crossing those fields mentioned above.

From the perspective of new machines designed for healthcare, motion assistance or rehabilitation, the main challenge is that existing machines tend not to provide user-friendliness, as well as sufficient safety. Meanwhile, the relatively complex operation leads to the conservative attitude of the elderly, who think that new machines like robots may not be easy to control. For example, the joint mechanism of exoskeleton robots cannot provide biomechanically similar motion function, which means that it is not likely to reproduce human natural motion, possibly resulting in user discomfort. Some improvements have been carried out on exoskeleton robots to better mimic human motions and enable easier joint movements, but limitations still exist [148], [149]. Furthermore, ethical and legal issues should also be taken into account since the application of new machines like exoskeleton robots or prosthetics involves the privacy of the wearers. Also, such technologies could be used to enhance one's physiological strength so as to turn humans into weapons [150]. Thus, a major research direction for new machines is to achieve better integration with human beings so that they can provide better service without physical and mental barriers in the CPS-HRS.

C. Fog Computing for Healthcare 4.0 and Healthcare IoT Systems

Patients interact constantly with surroundings during regular daily routines. In a typical IoT-enabled healthcare system, these activities are registered to the device layer that gathers diverse information ranging from vital signs to environmental and contextual information. All of these sensor data are then transmitted to and processed by a local set of computing devices, called fog nodes, within a fog layer [151]. These devices perform various processing on the received raw data and then transmit processed data to the cloud layer where long-term storage and statistical modeling can be easily implemented. This flow is described in Fig. 7.

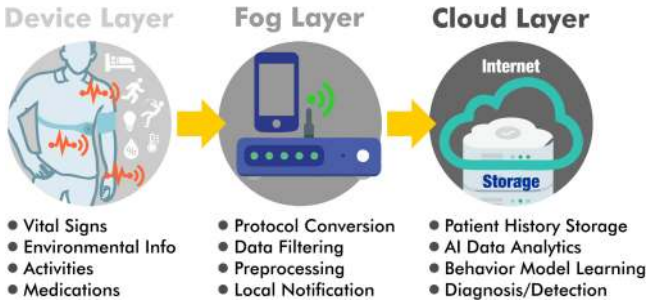

Fig. 7. Architectural elements of healthcare IoT systems.

Such ubiquitous healthcare systems need to deliver services to end-users demanding a satisfactory Quality of Experience (QoE), which poses tremendous challenges in the face of dynamic variations at multiple scales of the system stack: at the application, network, resource, and device levels. A key mechanism to manage and exploit these variations is personalization and holistic coupling of both the system (e.g., IoT) infrastructure, and the services provided to end-users [152]. Future research needs to be conducted towards self-aware cognitive architectures that delivers acceptable QoE by adapting to dynamic variations in infrastructural compute, communication and resource needs, while also synergistically learning and adapting to end-user behavior. This calls for leveraging technologies such as Fog and Edge Computing [153], [154], [155] to introduce intelligence and adaptability in integrated multiscale ubiquitous healthcare systems which are often based on the IoT paradigm. Novel solutions are required to efficiently manage information acquisition, communication and processing across different scales of the IoT systems [156]. These solutions need to implement cognitive behaviors by getting feedback from current status of the user and the context where it is located and collaborate to perform estimation and control tasks under resource constraints, while delivering personalized QoE to end users.

The capability of personalization is becoming essential since research directions of AI are towards individual services rather than generic services for a group of people [157], [158]. The future AI is attempting to target individual user by supporting customized learning and inference based on a huge amount of personal data. That is, cloud for AI must be able to assist these individual AI services by collecting and analysing vast amount of personal data for individual learning and inferencing. Hence, the system should be capable of 'personalization'. In order to provide the personalization services, it is necessary to understand the 'situation' of each patient, including their health risk and level of need of acute care. However, it is not

straightforward to understand the situation of a user in the real world. Indeed, we need to apply and enhance the state-of-the-art in collecting and processing a huge amount of sensor data around users in a multi-dimensional manner. Personalization becomes more challenging as the heterogeneity and geographic dispersion of data increseas along with the user base.

D. Cloud Computing and Communication

The Cloud plays a very important role in the healthcare system since all collected data will be sent to the cloud layer for the final processing. In Healthcare 4.0, the offloading technology in the fog layer will reduce some of the computing load in the cloud layer. However, there are still some critical challenges in the cloud layer for future CPS-HRS systems.

The first challenge is the heavy pressure brought by more and more AI and machine learning tasks in Healthcare 4.0. Different from general cloud computing tasks, AI and machine learning tasks can be dramatically accelerated by specific hardware. Some cloud providers bring graphics processing units (GPU) or tensor processing units (TPU) for acceleration [159], [160]. Since it is very difficult to manage this specific hardware in small granularity as general computing resources, the efficiency of the cloud layer is limited for processing a large number of small tasks in CPS-HRS. Two solutions are adopted for scheduling hardware resources, including hardware virtualization and small size hardware [161], [162]. However, there is still a need for novel solutions for scheduling healthcare tasks in the heterogeneous cloud layer for better energy consumption and higher processing performance.

Another challenge is the communication between the device layer and the cloud layer. The latency requirement of CPS-HRS tasks is much stricter than the general computing tasks in the cloud layer and a large amount of multimedia data needs to be processed in real-time. One solution is offloading computing tasks from the cloud layer to the device layer or fog layer. However, the task offloading depends on the type of applications. Because CPS-HRS applications are different from the traditional ones, it needs new task offloading mechanisms. Some novel solutions focus on offloading the AI and machine learning tasks into the device layer or fog layer by introducing new computing models [163]–[165]. Another solution is optimizing the task scheduling in the cloud layer according to the geographic position and latency requirement of each CPS-HRS task [166]. Although many existing works try to optimize the communication between devices and cloud servers, it still needs better solutions such as new architecture or protocols to connect these two separated layers.

IX. Conclusion

This paper was carried out to give new visions of the CPS-HRS with distinguishing features enabled by the closed loops. The current state of evidence related to the implementation of enabling technologies for the CPS-HRS has been described, providing insights into the suitability of each one of the techniques in the CPS-HRS. These new visions have been extracted from the review of more than 150 references, where the most relevant methodologies have been identified. This paper reports clear evidences that the CPS-HRS presented here could provide valuable tools for in-home care services, and that there is still room for improvements and relevant contributions. We hope that this work provides a valuable guide for researchers to make advances in the CPS-HRS.

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