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A Review on Challenges in Telerehabilitation and Human Activity Recognition Approaches during Covid-19 Pandemic

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ABSTRACT

Impact of COVID-19 pandemic is widespread imposing limitations on the healthcare services all over the world. Due to this pandemic, governments around the world have imposed restrictions that limit individual freedom and have enforced social distance to prevent the collapse of national health care systems. In such situation, to offer medical care and rehabilitation to the patients, Telerehabilitation (TR) is a promising way of delivering healthcare facilities remotely using telecommunication and internet. Technological advancement has played the vital role to establish this TR technology to remotely assess patient's physical condition and act accordingly during this pandemic. Likewise, Human Activity Recognition (HAR) is a key part of the recovery process for a wide variety of conditions, such as stroke, arthritis, brain injury, musculoskeletal injuries, Parkinson's disease, and others. Different approaches of human activity recognition can be utilized to monitor the health and activity levels of such a patient effectively and TR allows to do this remotely. Therefore, in situations where conventional care is inadequate, combination of telerehabilitation and HAR approaches can be an effective means of providing treatment and these opportunities have become patently apparent during the COVID-19 outbreak. However, this new era of technical progress has significant limitations, and in this paper, our main focus is on the challenges of telerehabilitation and the various human activity recognition approaches. This study will help researchers identify a good activity detection platform for a TR system during and after COVID-19, considering TR and HAR challenges.

Keywords: COVID-19; telerehabilitation; human activity recognition

INTRODUCTION

The World Health Organization (WHO) declared the coronavirus outbreak a global public health emergency at the end of January and confirmed it a pandemic on March 11, 2020 (Akmam et al. 2021). The World Confederation for Physical Therapy suggested to provide only the crucial rehabilitation during the pandemic (Turolla et al. 2020). Because of such restrictions, Telerehabilitation (TR) can be considered as a worthy alternative method of consultation and rehabilitation. Figure 1 exhibits weekly confirmed COVID-19 cases per million people from January 27, 2020 to November 21, 2022.

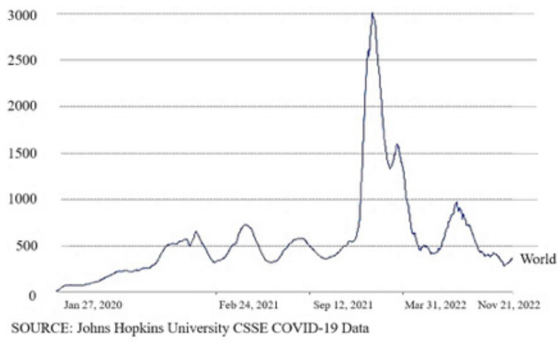

FIGURE 1. Weekly confirmed COVID-19 cases per million people

Human activity recognition (HAR), one of the many rehabilitation services offered by TR systems, is a core part of treatment for medical conditions like parkinson's, stroke, musculoskeletal injuries and so on. HAR intends to develop a system that can detect and describe human actions by mimicking the human visual system (Abu-Bakar and Syed 2019). HAR may be categorized in three main groups, namely, sensor-based, vision-based, and multimodal (Ankita et al. 2021). Figure 2 outlines several HAR approaches.

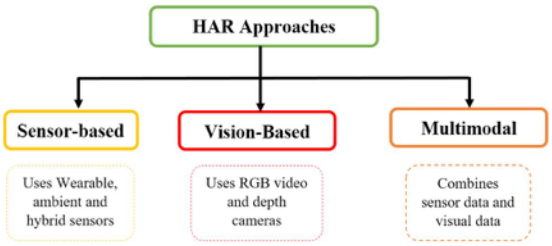

FIGURE 2. Various approaches of HAR

With the use of TR, these methods can be used to assess various human activities remotely during pandemic. However, it is difficult to put into practice as HAR approaches aren't without their deficiencies. Also the TR system have its own set of benefits and downsides (Ankita et al. 2021). This work is specifically targeted towards the challenges of TR and these HAR approaches. The rest of the paper has been organized as follows: TR during Covid-19 and various HAR approaches have been discussed next two sections. The discussion part has focused on overall discussion on challenges or limitations related to TR and HAR approaches. And finally, this review paper ends with the concluding remarks mentioned in the conclusion section.

TELEREHABILITATION AND COVID -19

Rehabilitation is a process of returning patients to normal life using training and therapies. And rehabilitation using telecommunication and internet is known as telerehabilitation or e-rehabilitation. Conventional rehabilitation process may expedite the spreading of COVID-19, so TR can be considered as a good alternative to ensure the health services to patients. Chang et al. (2020) mentioned that remote rehabilitation can be considered as a useful way for patients who needs rehabilitation and care after stroke during the COVID-19 pandemic. Rabanifar et al. (2021) pointed out the advantages of TR such as less logistical hurdles, better patient autonomy, harmony with remote monitoring, virus protection, customization options, and so on. TR has decreased transportation concern, travel and waiting time, travel expense, physical barrier and caregiver burdens, staying time in hospital, use of emergency medical services and so on (Fiani et al. 2020). Many researchers have also given focus on various advantages of TR in their researches. Figure 3 depicts the basic telerehabilitation architecture.

FIGURE 3. Telerehabilitation System Architecture

Despite the many positive aspects, TR does have a few downsides as well. Ciortea et al. (2020) mentioned that though the use of TR is expanding, the major obstacles are raising patients' acceptance of the new approach as well as their motivation and engagement throughout the program. Budgetary limitations, data security and reimbursement difficulties, understanding deficiency and discomfort with the use of new technology were all cited by Brigo et al. (2020) and Rangachari et al. (2020) as significant impediments to TR implementation. Zedda et al. (2020) addressed most significant TR related challenges which includes adaptability to various rehabilitation setups, economic sustainability of the suggested solutions, scalability, compliance and patient participation. Apart from the numerous advantages, of TR, Falvey et al. (2020) identified that cost is the most crucial aspect in the development of TR systems. Kairy et al. (2017) mentioned that due to a lack of understanding, healthcare professionals are less aware of the benefits of TR application in real life. Few factors related to TR were mentioned by Bahari et al. (2019) such as disappointment and reluctance, expense, technological limitations, connectivity issues, less planning and training knowledge, lack of awareness, skill optimizing and e-healthcare knowledge. Tyagi et al. (2018) stated about the advantages of TR such as easy accessibility, continuous monitoring of patients etc., but also focused on few barriers such as equipment setting problem, physically test constraints, connectivity issues, disability along with age and sensory impairments. Because of these obstacles, the implementation of TR systems to aid in patients' recoveries during the COVID-19 has turned out to be challenging.

Table 1 displays the attitudes and willingness of both physiotherapists and the general people toward TR during and after the pandemic event. According to the information provided articles in table 1, despite the fact that this system is afflicted by a great number of obstacles, TR's popularity has not decreased since the outbreak.

TABLE 1. Perceptions and willingness of physiotherapists and general people towards TR

Author	Year	Physiotherapists (Positive)	General People (Positive)	Country	Total Participants (Physiotherapists+ General People)
Caroline et al.	2020	-	62%-75%	Belgium	200 (0+200)
Almojaibel et al.	2020	79%	-	Worldwide	222 (222+0)
D'Souza et al.	2021	72.9%	-	India	118 (118+0)
Dierick et al.	2021	50%	75%	Belgium and France	175 (68+107)
Fernández et al.	2022	50%	86%	Brazil	1107 (707+400)
Ramanandi	2022	66.84%	-	India	389 (389+0)
Buabbas et al.	2022	-	93.5%	Kuwait	46 (0+46)

HUMAN ACTIVITY RECOGNITION (HAR) APPROCHES

HAR recognizes a variety of human actions including walking, running, sitting, sleeping, standing, showering, cooking, driving, door opening (Chang et al. 2020 & Minh Dang et al. 2020) and specific arm movements such as reaching/releasing an object, frontal elevation and elderly people's activity (Demrozi et al. 2020). Based on the types of devices and sensors used, its approaches can be divided into wearable, visual, and multimodal categories. Different sensors and equipment utilized in HAR are shown in Figure 4.

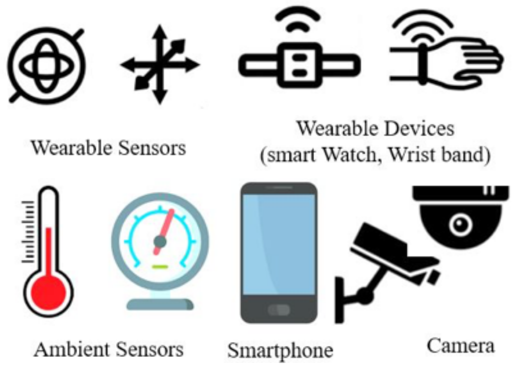

FIGURE 4. Sensors and devices used for HAR

WEARABLE SENSORS

Wearable sensors accumulate physical and motion information, allowing endless checking of a patient's state. Optical, stretch, pressure, chemical, IMU, bio-potential, and other sensors are used in diverse ways in physical and HAR solutions (Jalloul and Nahed, 2018).

Inertial Measurement Unit (IMU): IMUs are made up of accelerometers, gyroscopes, and magnetometers which are the most widely used and acceptable sensors in HAR. Nearly every trendy gadget, including Wii controllers and virtual reality (VR) headgear, uses inertial sensors for various purpose. Micro-electromechanical system (MEMS) technology is the foundation of these sensors' current component. Miniaturization and growth in MEMS have lowered sensor size, weights, and costs, benefiting most new applications (Tamura 2014 and Sultana et al. 2022). These sensors are getting smaller and smaller and can be easily integrated into outfits, smart glasses, and other wearables (Zhan et al. 2015; Gummeson et al. 2014 & Leonov 2013). An upper body activity recognition model was developed by Lim et al. (2021) using deep ConvLSTM architecture with reduced number of sensors which was recommended as a useful way for assessing home-based rehabilitation. Various kinematic parameters related to functional movements and activities were analyzed by Ponvel et al. (2019) and Zainal et al. (2018) suggested a simple, economic and reliable system which can be used to get these parameters using IMU sensors.

But, despite these strong advantages, inertial sensors pose a number of significant complications. Yang et al. (2019) introduced a new wearable device that uses both IMU and pressure sensors to improve activity recognition accuracy. However, they underlined constraints such as air pressure sensor leaking, long-term fall off, and incorporating other daily activities like riding an elevator. Fu et al. (2021) stated that attention should be paid to fall detection, sensor structure optimization, and the use of several nodes to recognize more complex motions, such as gait identification and step distance measurement. An in-depth survey was conducted on HAR techniques, datasets, and algorithms by Jobanputra et al. (2019). They determined that no single strategy is best for distinguishing any activity because it depends on several aspects. Multiple sensors usage, sensor placement, multiple activity recognition, and inaccurate sensor data were recognized as research gaps connected to sensors. A new activity recognition algorithm based on a head-worn IMU was proposed by Cristiano et al. (2019), where authors mentioned that body postures identification in real-life situations, elderly people's head acceleration pattern, inclusion of other body movement and systems (headphones, headbands, and eyeglasses) all should be considered as future research considerations. X. Zhang and Zhang (2019) carried out a detailed survey on HAR employing several sensors. According to the authors, each type of sensor is best suited for a certain metric, and the more challenging reliability and accuracy problems may be solved using the sensor fusion technique. The drifting problem was noted as a serious issue by Elbasiony and Gomaa (2020). Seel et al. 2020 noted several IMU-related challenges including sensor signal processing challenges, sensor-to-segment alignment or calibration issues, rigidity of sensor connection, magnetic disturbance particularly in indoor environments, signal corruption by errors and measurement noise. Pacher et al. (2020) identified four distinct types of calibration procedures as well as different lower-body segment ideas. However, they concluded that determining the appropriate approach for sensor-to-segment alignment or calibration is difficult. Rahn et al. (2021) observed an overall prediction rate of human activity detection using a smartphone and an IMU sensor, but they faced problems recognizing a few activities for a few sensor locations. A current state-of-the-art in HAR was reviewed by Chang et al. (2020) and they identified a few drawbacks of wearable sensors, including discomfort for aged, forgetting to wear the sensors, deployment issues in large-scale applications and restrictions on motions. Reich et al. (2020) stated that for best performance, information about specific amount and combination of IMUs is not possible. Few researchers have reported that wearable sensors have shortcomings such as high energy consumption, noise production, limitations in large-scale applications, movement limitations, high cost, complexity, and fusion difficulties (Atallah et al. 2011). Battery life limitations, arbitrary signals associated with activities, and other inertial sensor issues were addressed by Hassan et al. (2018) & Anwary et al. (2018). In addition, a detail understanding of biomechanics is required for the study of the performance of human activities, as well as for the treatment of rehabilitation patients and the development of rehabilitation equipment using any one of the HAR approaches (Ramlee et al. 2017 and Ramlee et al. 2018). Without this understanding, the outcomes of the IMUs will be significantly altered, which might be interpreted as a significant problem for these systems.

Smartphone: It is simple to monitor user behaviors using integrated sensor data from smartphones, as, at present, smart phones have become everyone's companion. It has a variety of sensors such as accelerometer, gyroscope, barometer, proximity sensor, and others (Mahanta et al. 2020).

However, from a technical standpoint, the smartphone-based HAR suffers from deficits. Bugdol et al. (2016) aimed to reduce the error rate of activities recognition for upstairs and downstairs. However, their accuracy for running and jogging is poor and they failed to account for semi-complex and complicated activities such as cooking, dancing, and bus travel. Chen et al. (2020) gave importance on complex activities recognition and smartphone orientation. Tradeoff between the number of sensors in smartphone and performance, location of smartphone and other sensors, discomfort and forgetting to keep phone continuously were considered as challenges by Antar et al. (2019). The authors also mentioned that future research should focus on memory, CPU, number of sensors, battery consumption, trade-offs between recognition accuracy, precision, detection of the most similar activities, and the employment of a group of classifier-based technique as they are still regarded as challenges. Choudhury et al. (2021) presented a new HAR method considering physical properties, such as height and weight, but complex activities and other physical properties were not considered in this work. A novel approach was proposed for HAR by Uddin and Torresen (2019) and they found postural transitions as most challenging actions while using smartphone sensors. Problems such as cross-device, cross-locations, and automatic determination of the threshold which is important for designing a HAR model were mentioned by Deng et al. (2014). Placement of sensors on the human body was considered as a critical issue by Ustev et al. (2013) since the degree of movement in different parts of the body for the same activity varies, and it may include different signal information. Concone et al. (2017) cited few challenges such as filtering out noise data acquired just before or after an action and recognizing complex activities made of basic tasks. Problem related to recognition of multiple tasks at the same time were discussed by Khan et al. (2011), however they stated that in the context of multitasking, sensor predicts the dominant activity only. According to Ferrari et al. (2021), the increase in sensor numbers and types, which allows the availability of more data sources, may represent a difficulty in terms of heterogeneity, because not all devices and sensors have the same requirements.

TABLE 2. Wearable sensors and their applications

Wearable sensors	
Types	Applications
• Bio-potential sensors (Electroencephalography caps, Electrocardiography chest strap, Electromyography bands)	• Activity and fitness monitoring • Fall detection
• Optical sensors (Glasses, Contact Lenses, Cameras)	• Seizure and cardiac arrest detection
• Stretch and Pressure sensors (Textiles, Belts and bras)	• Therapeutic exercises
• Chemical sensors (Electronic skin, Textiles)	• Treatment efficacy
• Inertial Measurement Units (Wristbands, Smart watches, Body fixed sensors)	• Disease progress • Monitoring of early health signs

Smart Watch: Sensors in smart watches can offer physical, behavioral, and ambient information. They have the advantage of mobility, universality, and use of several sensors which facilitates multimodal large-scale investigations in everyday life. In terms of sensor and signal quality, these technologies have yet to catch up to medical-grade devices, and there is no universal device that can be used for all purposes (Saganowski et al. 2020). The accuracy of wearable devices like smart watches are inconsistent and difficult to compare and device provides different accuracy in measuring different quantities as mentioned by Cosoli et al. (2020). In comparison to chest-strap devices, wrist-worn devices have an issue with accuracy and dependability during high-intensity sports, according to Seshadri et al. (2019). Wrist-worn devices can count steps, but unfortunately their performance is often inferior to that of benchmark detectors and errors are there at modest walking speeds (Fokkema et al. 2017). Weiss et al. (2019) used smartphone and smart watch together for best biometric performance. However, they mentioned about adding many additional activities, establishing a two-stage biometric system, feature normalization and selection to their proposed system for better outcome. A continuous online and offline human activity detection system with better accuracy was proposed by Ashry et al. (2020) using smart watches where authors pointed to focus on using many smart watches to collect dataset of human interactions such as handshakes and scrimmages, as well as sporting events such as boxing. To detect out-of-distribution of HAR with smart watch IMU, a method was proposed by Boyer et al. (2021). But there was dataset preparation deficiency. It was limited to track shoulder physiotherapy and priority were not given to focus on isometric exercises and magnetometer data. In order to recognize human behaviors, Mozaffari et al. (2020) regarded a smart watch as a new IoT solution, and their experiment revealed nearly 99 % accuracy. However, data from elders and vulnerable persons participating in outdoor and more typical everyday activities were not considered which ensures more reliability. Smart watches have limited resources in terms of power consumption, memory, storage, processing capability, accuracy, and there are functional limitation on continuous use, as well as diversity in smart watch usage patterns among age groups (Zimbelman and Keefe 2021). A real time 3D arm motion tracking using smart watch was proposed in (Wei et al. 2021), where they mentioned about torso motion as a challenge as it may affect the tracking accuracy. While proposing a smart watch-based fall detection system by Bi et al. (2020), authors failed to properly classify Activities of Daily Living (ADLs), particularly sitting and walking. A system for identifying pen-holding gesture using smart watch was proposed by Mauldin et al. (2018), which is not suitable for cursive writing and the system is limited to only slow writing right handed people. Table 2 summarizes various wearables and their applications.

VISION-BASED RECOGNITION

When compared to the sensor-based technique, the vision-based approach offers more precise recognition. However, vision-based techniques have their own drawbacks, such as high cost, complexity, and privacy concerns and this technology is not frequently employed in healthcare monitoring systems (Ranasinghe et al. 2016). Prarthana and Prasad (2020) mentioned about various techniques involved in vision-based activity recognition. In addition, they mentioned some shortcomings of the vision-based system such as concurrent and interleaved activity recognition problem, ambiguity in interpretation, difficulty in detection of different motion patterns of different subjects at different time, classification algorithm challenge to recognize the motion during the transition period between two activities, and complex activities recognition problem. Zakaria et al. (2022) mentioned about the data acquisition problem and Abu-Bakar and Syed (2019) recorded problems related to RGB or color-based images such as changes in illumination, background clutter, pose variability, and appearance (texture) dependency which can be eliminated by using RGB-D and skeleton based cameras. But RGB-D cameras such as Kinect have significant drawbacks, such as a higher complexity, cost, etc. (Chen et al. 2020). Some vision based HAR related problems or challenges such as same working pattern, inter class variability and similarity, change in illumination, shadow effect, partial or full occlusion, self-occlusion, scaling, bootstrapping, camera jitter and automatic adjustment, noisy frame in video, camouflage, movement of objects or human being in background were recognized by D'Sa and Prasad (2019). The lighting of the surroundings may have an impact on vision-based approaches, which in turn restricts the application scenarios, particularly in the mobile context. Additionally, this method requires a camera, which can sometimes be expensive (Naosekpam et al. 2019). Anthropometric variations, image-quality, frame-rate issues, multi-view variations, poor weather condition, insufficient data, camera motion, illumination variations, dynamic and cluttered backgrounds were mentioned as challenges in vision based HAR (Jegham et al. 2020). S. Zhang et al. (2017) emphasized on the significance of input image quality, input information balance, algorithm efficiency and its recognition rate, as well as combining various datasets and the use of LSTM with ConvNets architecture for activity video analysis. H. B. Zhang et al. (2019) mentioned about many confounding issues of vision based HAR, such as the diversity and complexity of body postures, occlusion, and background clutter for human action recognition, deep learning challenges for multimodal, interaction recognition problems, and fast action detection in the spatiotemporal dimension. Lighting variation, occlusion, benchmark dataset unavailability, cost, similarity between classes, and distinction between voluntary and involuntary activities were listed as challenging issues of vision based HAR by Beddiar et al. (2020). Colorimetric segmentation, which might cause human body parts to be confused with scene objects, was addressed by Xu and Lee (2015). Collings et al. (2015) and Hu et al. (2004) discussed issues related to people's appearance or outerwear that obstruct the correct operation of HAR recognition as well as the scale variation problem. Akmam et al. (2021) mentioned about data acquisition as one of the main motion analysis research challenges. The difficulty of equipment integration at home for tracking, which is perceived as a violation of intimacy and privacy, was discussed by Bhardwaj and Singh (2016).

DISCUSSION

From the literature review, it is evident that the use of telerehabilitation technologies come with a number of advantages, but also suffers from significant drawbacks. Sensor-based techniques offer a variety of benefits, including minimalism, easy installation, more flexible, low cost, light weight, and it provides detail of human activity and behaviors and has no issue related to privacy. Vision-based solutions have several advantages, such as it can record a large screen with a single camera and supplant multiple sensory devices with a single camera, high accuracy and so on and these systems do not require intervention or physical contact. These approaches, however, also have a number of shortcomings. A summary of challenges related to the TR and various approaches of HAR, mentioned in the above literature survey, has been listed in table 3.

Based on the information presented here, it is plausible to assert that telerehabilitation (TR), despite its many disadvantages, has the potential to be a useful alternative for receiving rehabilitation remotely and also the analysis of the patient's activity can be carried out remotely employing this TR in conjunction with any of the available HAR approaches. But, it is challenging to arrange and set up the system's equipment in the case of vision-based system designs, and also the need for professionals to operate the system remotely at home has made this approach more challenging. There are also some severe issues with the camera based system, including the violation of patient privacy, and the high cost of systems. Nonvisual sensor approaches do not have these issues that are associated with vision-based systems, and as a result, they perform significantly better than that of vision-based HAR technologies. Despite this, one should pay attention to the problems that are associated with wearable devices so that it can be incorporated with TR for providing rehabilitation remotely with more effectiveness.

TABLE 3. Challenges of TR, and various approaches of HAR

		Challenges
TR		Implementation and maintenance cost, technology and equipment adaptation and understanding for both patient and healthcare professionals, communication barriers, face-to-face contact, patient participation, equipment, training, exercise limitation and lack of awareness.
Wearables	IMU	Long-term activity monitoring, quantity and position of sensors, battery life, signal corruption by arbitrary signals/noise/errors, large-scale applications and movement limitations, sensor fusion, aged people's adaptability, calibration, drifting, accuracy and complex activities detection.
	Smart-phone	Semi-complex and complex activity detection, quantity and selection of smartphone sensors, smartphone location and orientation, continuous use, battery consumption, memory, similar activity detection, noise and recognition of multiple tasks at the same time, wrong activity detection due to location variation.
	Smart Watch	No universal device, accuracy and dependability, measurement errors, limited resources in terms of power consumption, memory, storage and processing capability, continuous use, diversity in smart watch usage patterns among age groups, torso motion and challenges with simple activity recognition issues.
Vision Based		Concurrent and interleaved activity recognition, interpretation ambiguity, difficulty in different motion pattern detection of different subjects at different time, classification algorithm challenge during transition period between two activities, complex activities recognition, illumination, background clutter, pose variability, higher equipment complexity and cost, inter and intra class variability and similarity, partial/full/self-occlusion, shadow effect, camera jitter, camera motion and automatic adjustment, noisy video frame and frame rate, camouflage, background object or human movement, anthropometric variations, image-quality, multi-view variations, fast action detection, colorimetric segmentation, outerwear, equipment integration problem and violation of intimacy and privacy.

Also the survey results will assist the researchers to identify a suitable detection platform for the TR system during and after the COVID-19 crisis, based on the need and the various obstacles associated with TR and HAR techniques.

CONCLUSION

In this study, the necessity and limitations of a TR system and various Human Activity Recognition (HAR) approaches during this COVID-19 pandemic situation have been analyzed and here TR has been regarded the only alternative approach to provide remote healthcare services with technical support. Various approaches of Human Activity Recognition (HAR) systems for TR have been investigated. The limitations of wearable sensors, specially IMU, smartphone, smart watch and vision-based activity detection systems, have also been highlighted where wearable technology has shown to be a better approach for providing people with support services, considering some critical limitations of vision-based systems such as privacy issue.

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DECLARATION OF COMPETING INTEREST

None

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