A Smart and Secure IoMT Tele-Neurorehabilitation Framework for Post-Stroke Patients

Soumya Kanti Manna, M. A. Hannan Bin Azhar, and Mohamed Sakel

Abstract COVID-19 pandemic adversely challenged the healthcare system in an unprecedented way. Access to neurorehabilitation programme for patients with stroke and other neurological disability was severely restricted including shutting down of most community-based and outpatient facilities. There is hardly any organised virtual programme of exploring any potential of stretching and exercising of muscles needed in a rehabilitation programme. There is an impetus to innovate service developments, while the risks and fear of contracting the coronavirus remain prevalent. We propose a framework for developing a novel tele-neurorehabilitation system that will guide the patients to perform therapeutic exercises, as proposed by the clinicians, remotely. The system will allow patients to directly interact with doctors through a secure audio–video online portal. Wearable motion tracking sensors will be integrated within a hardware-based home setting for gathering performance data live from patients while they are performing exercises. The paper describes the design components of the framework justifying the tools, hardware, and protocols required to implement a secure online portal for tele-neurorehabilitation. Specifications of the core architectural layers have been reported. Some preliminary work demonstrates how the framework specifies capturing and analysing of physiological data using wearable sensors, as well as displaying of gait parameters on a software dashboard.

Keywords Tele-neurorehabilitation · Stroke · Joint parameters · IoMT

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1 Introduction

COVID-19 pandemic adversely impacted post-stroke rehabilitation for a number of reasons including diverting clinicians to urgent COVID care, closure of outpatient and community-based programmes to reduce infections and fear of disabled patients to attend hospitals. World Health Organization (WHO) estimated the total number of new COVID-19 cases to be more than 1.3 billion with 27 million deaths worldwide [1]. Hospitals in UK prioritised care for COVID and emergency patients only [2]. Currently, there are 80 million stroke survivors in the world [3]. They require ongoing rehabilitation programme for reducing neuromotor disabilities. Such programmes were mostly shut down during the pandemic. Video-based consultations started quite early in the pandemic. However, there is no software tool to provide post-stroke therapies to patients remotely via telerehabilitation which would include rehabilitation exercises that are personalised, complex and interactive. The anticipated limitations and challenges for any apps to assist telerehabilitation would include design, usability, functionality and security features [4]. The scope of remote treatment using tele-medicine is widely accepted among healthcare professionals, as it facilitates real-time interaction between doctors and patients in a remote location [5]. During COVID pandemic, doctors and healthcare workers used several smartphone applications to provide diagnosis and instructions to patients virtually [6]. It reduces human contact and is safer, since it obviates the need for patients and carers to visit hospitals. Telerehabilitation could potentially enable doctors to provide patients with instructions, monitor the performance of patients and provide feedback quickly.

There are only a few projects so far to facilitate and explore telerehabilitation. Tan [7] conducted a telerehabilitation experiment on 52 stroke patients, where half of the patients experienced conventional in-person rehabilitation sessions, and the other half experienced telerehabilitation via video conferencing with a therapist. There was no difference in physical function and independence in movement among the two cohorts of patients, although the experiment only focused on one type of stroke and did not take severity into account. A study conducted by Sarsak [8] explored the effects of telerehabilitation on different sets of post-stroke patients with mobility impairments using videogame-based virtual reality rehabilitation system. They found that the therapist located 100 miles away could accurately assess the functional needs of patients and prescribe suitable devices for them. The system was conducted over the Internet with personal computer-based cameras. Another game-based telerehabilitation method was conducted using Kinect-based system (KiReS) [9]. The system could monitor patients, while they perform their assigned tasks using a Kinect sensor. Evaluations were carried out by an exercise recognition algorithm and presented to the user interface to allow feedback. However, all these telerehabilitation systems lack several necessary functionalities, such as assessing necessary joint parameters during an activity, e.g. gait, posture, spasticity, torques, stiffness, walking patterns, neuromotor functions and balances. These systems also lack storing and feeding real-time performance data to doctors and patients. None of these tools had proactive artificial intelligence (AI)-assisted prediction and guidance for estimating abnormalities and recovery rate of users. A concern exists regarding full stack security at hardware and software levels. There is no such customised online guiding tool available for specific stroke-related therapy to influence joint spasticity and stiffness, which hinders recovery. It is possible to incorporate non-invasive wearable sensors and motion tracking sensors into an online tool for monitoring and recording patient's performance during therapy. To facilitate post-stroke therapy remotely, this paper reports a framework to develop a state-of-the-art telerehabilitation tool which not only guides patients for post-stroke therapy but also assesses their performances to estimate their recovery rates and patterns. It integrates three platforms together (standardised exercises, live audio–video interface with the rehabilitation expert and motion tracking sensor) to guide stroke patients through the rehabilitation training at patient's home. The tool will also include interactive game-based therapy, e.g. audio-visual (AV) guidance during exercises, group-based exercises, performance scores, etc., to increase motivation and engagement for patients to participate in the rehabilitation programme.

2 Design Framework

The framework (Fig. 1) represents a secure online platform for patients, doctors, healthcare workers and technical support providers to be connected supporting telerehabilitation. A novel tele-neurorehabilitation tool will be developed where specific exercises will be shown to patients without involving rehabilitation experts, instead post-stroke therapy will be guided by an AI-assisted software. The list of specific exercises required for stages of rehabilitation, guidelines, and instruction for delivering the exercises will be prepared by the rehabilitation experts at the East Kent Hospitals University NHS Foundation Trust, UK. All types of exercises will be programmed into this online tool using simulated avatar's movement. In case patients need any help, they can still contact the experts using a live AV feed through a secure channel.

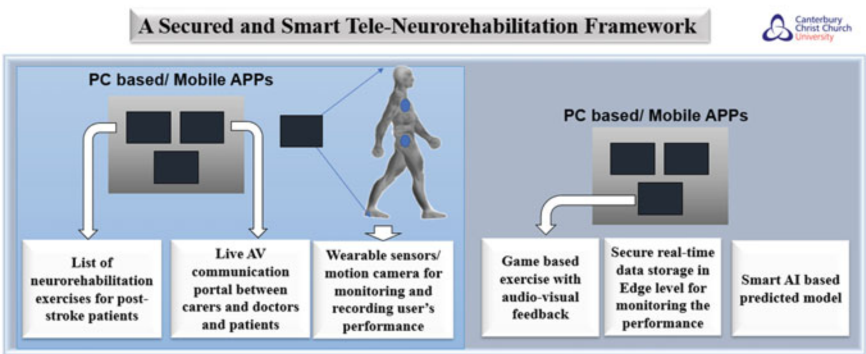


Fig. 1 Tele-neurorehabilitation tool

Non-invasive wearable sensors and motion capture cameras will be connected to the rehabilitation tool for acquiring and recording patient's performance during the therapy. Recorded data can be further compared with optimum parameters, and a predictive model will be developed using machine learning algorithm to estimate the recovery rate for an individual patient. Thus, in the process of therapy, it is possible to consistently assess recovery by comparing performances between present and past health conditions.

Due to the capture of patient's sensitive data by the tele-neurorehabilitation tool, appropriate security design must be incorporated in the framework. Figure 2 shows three layers of the system: device, edge and cloud, and the framework includes security components in all of these three layers. Device layer refers to the hardware level of the Internet of Medical Things (IoMT) solution, where hardware architecture-level security will be implemented by incorporating a secure crypto processor and secure booting technique to ensure system integrity to stop unauthorised modifications of data and the system environment [10]. Physical protection barrier will be also implemented by using physical shielding covering internal circuitry.

Due to sensitive nature of the data, while data are processed in transit (e.g. over the physical and network layer before reaching to cloud), unsecure communication can be susceptible to intrusions such as the man-in-the-middle attack; so, it is important that the framework should include strong secure encryption techniques and an automated intrusion prevention system to detect unwanted intrusions and prevent malicious activities. A distributed system will be used where patient's data will be stored in an edge node, and healthcare providers will request for data with a secure transactional ID in real-time [11] through a cloud-based web portal. As patient's data are pulled on request, the profile information will be created dynamically on a cloud-based dashboard. The proposed distributed architecture for data storage and processing in the edge layer will have advantage over a centralised cloud-based solution, as the latter is prone to denial-of-service (DoS) attacks, where attackers can easily flood the system and attempt to shut down the server. The proposed secure distributed architecture will prevent DoS attack ensuring better response time of the systems.

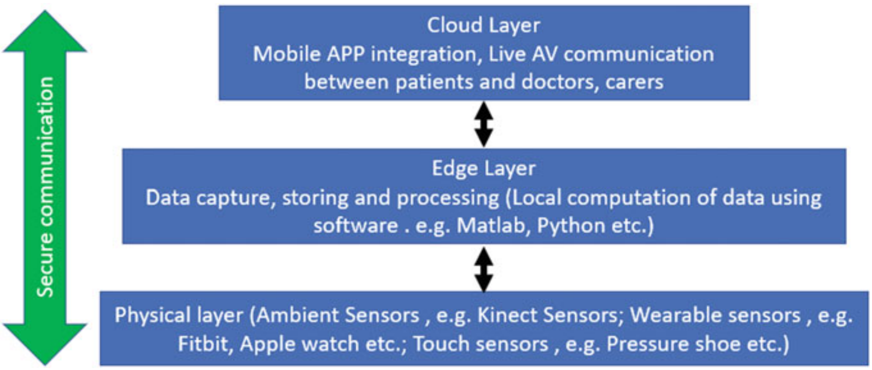


Fig. 2 Three layers of framework

2.1 Physical Layer

Physical layer (or ground layer) may consist of several physical sensors (Fig. 3), such as Kinect sensor [12], Intel depth camera [13], pressure sensor [14] and inertial measurement unit (IMU) sensors [15]. This array of sensors will be connected to an embedded controller for acquiring and recording patient's performance during the therapy. An insole pressure shoe consisting of force sensors and IMU will be developed for measuring gait analysis of users, such as profiling of strike and swing phases [14]. To demonstrate the measurement of the gait data during strike phase, we have developed a force plate (Fig. 4) consisting of four force sensitive registers (FSRs) connected at four major points under the feet.

Figure 4 shows the points under the feet where four sensors were connected: heel (FH), first and fifth metatarsal bones ($F1$, $F5$) and toe (FT). These locations are the most critical points for estimating gait cycle such as (1) heel strike, (2) foot flat, (3) heel-off and (4) toe-off [14]. These sensors will be used for measuring the distributed force under feet due to body weight while walking. As shown in Fig. 4, all FSRs are connected to analog pins of Arduino board using potentiometers. The voltage drop across the variable terminal of potentiometer has been measured and calibrated against the known force. Use of Arduino is feasible for developing the prototype system as it usually takes 0.1 ms (millisecond) to read the signal from force sensors. The pressure range of the force sensors is around 0–175 psi, and the force accuracy is ± 5–$\pm$ 25% [16].

Kinect sensor will track human body joints and reflects joint vectors of a user. Currently, the new version of Kinect sensor $V2$ can track six people at a time and estimates 3D position of 25 joints of each user. The recorded data will be analysed

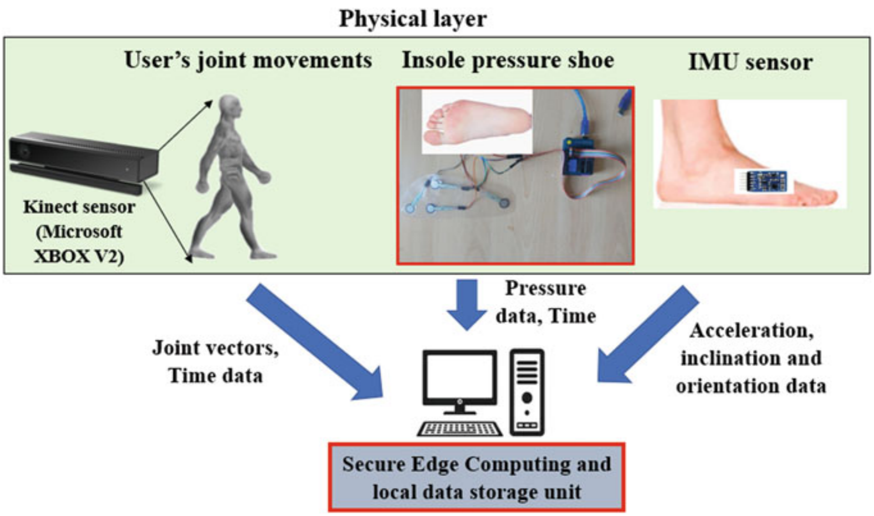
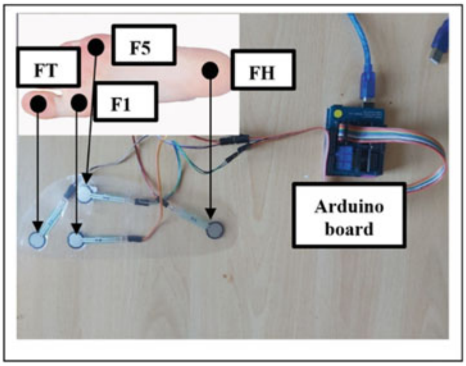


Fig. 3 Physical layer



Sensor points	
FT	Force sensor at Toe
F1	Force sensor at first metatarsal bones
F5	Force sensor at fifth metatarsal bones
FH	Force sensor at Heel

Fig. 4 Force plate and its circuit diagram

to generate important joint parameters (angle, velocity, posture, stiffness, spasticity, jerk and torque) as shown in Table 1. Combining the sensor data will make it possible to measure a patient's health status continuously.

2.2 Edge Layer

Edge layer (Fig. 5) will convert raw user's data into clinically useful information. This layer can be used for local computation along with filters and computing algorithms. The user's interaction model will provide a list of specific biomechanical exercises for stages of rehabilitation, and clinicians from the hospital will recommend the required therapy to influence joint spasticity and stiffness based on user's agreement and previous activities. User's performance data will be stored at the edge level. Historic patterns in the data will be analysed to train an artificial intelligence model to predict and guide the rate of recovery to the patients. The edge layer will also push notifications to doctor's critical conditions of patients, such as when joint parameters exceed a threshold limit. Due to distributed nature, several edge nodes can be connected and synchronised in this layer.

Preliminary work has already been done on how to create virtual reality-based rehabilitation game [12] and to analyse the recorded data for extracting important joint parameters [17]. Figure 6 demonstrates an example graphical user interface (GUI), which has been developed in a MATLAB platform. There are two sections in the GUI: user exercise module (UEM) and data monitor (DM). The UEM section is used for showing specific post-stroke exercise to patients and camera feed for recording user's activities, whereas the DM section is used for displaying and recording user's performance through wearable sensors and Kinect sensor. Patients will be able to view the exercises as integrated animations or videos to show the standard way to perform them. The platform also includes interesting features to enhance

Table 1 Measurable joint parameters

Joint parameters	Computation method	Sensor involved
Angle	Computed from the recorded 3D vectors of user's joints	Kinect sensor
Velocity	Computed by differentiating the joint angle with reference to time	Kinect sensor
Acceleration	Computed by differentiating the joint velocity with reference to time	Kinect sensor
Posture	Estimated by connecting adjunct joint vectors	Kinect sensor
Workspace	Computed by collecting the reachable Cartesian coordinates in 3D space	Kinect sensor
Torque	Calculated from rigid body dynamics of human body where the information of segment mass of user, distance of the centre of gravity are measured from user's anthropometric data, and joint parameters are measured from Kinect sensor	Kinect sensor
Jerk	Computed from the sudden change of joint torque over time	Kinect sensor
Stiffness	Calculated from joint torque and rotation angle	Kinect sensor
Spasticity	Computed from muscle contraction which depends on the stiffness or tightness of muscles	Kinect sensor
Gait (strike phase)	Accessed from pressure data using force sensors fitted under foot in an insole during strike phase	Foot pressure sensor
Gait (swing phase)	Calculated from joint velocity, acceleration, orientation and inclination measured by IMU sensor	IMU sensor
Walking pattern	Accessed from the combination of pressure data, acceleration and orientation	Foot pressure and IMU sensor
Footsteps	Computed from heel strike with respect to time frame	Foot pressure and IMU sensor
Foot orientation	Measured from the acceleration and digital compass attached to IMU sensor	IMU sensor

patient engagement in exercises, such as game-based activities. Audio-visual feedback will be incorporated into the game window, where users will be prompted with feedback when physiological parameters from sensors (Kinect + FSR + IMU) and user's voice are inputted.

The bottom left graphs inside the GUI (Fig. 6) shows the real-time pressure sensor data from four force sensors placed at the heel (FH), first and fifth metatarsal bones ($F1$, $F5$) and the toe (FT) as detailed in Fig. 4. The response time of these sensors is

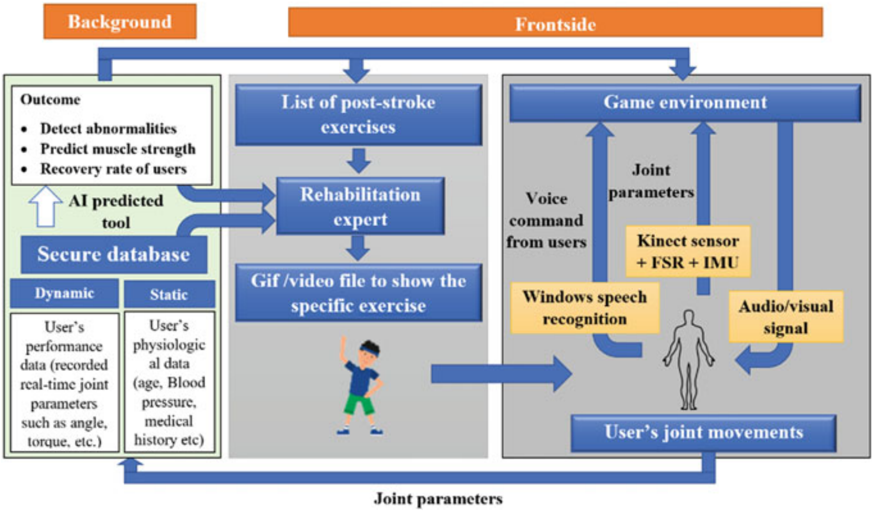


Fig. 5 Edge layer

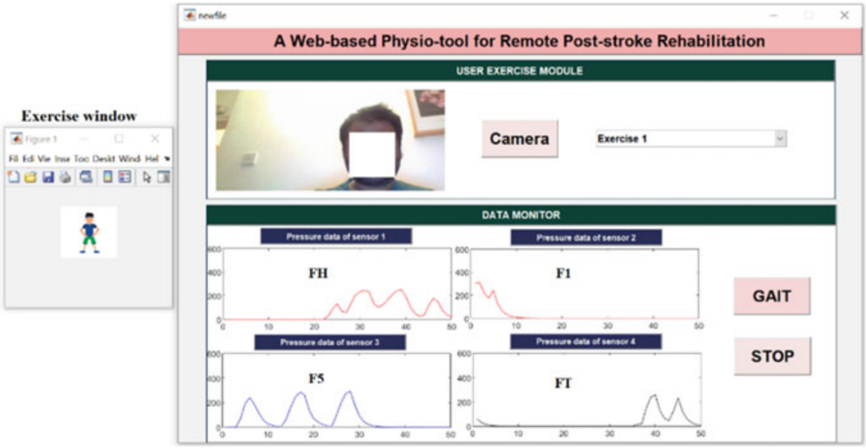


Fig. 6 Demonstration of graphical user interface (GUI)

near about 1–2 ms. The plots in the GUI demonstrate how the sensors work; however, it does not represent any gait information as we have not conducted any experiments with human subjects yet.

2.3 Cloud Layer

Healthcare professionals will use the cloud-based interface (e.g. web portal) to initiate secure connections and transaction with the edge node to pull patient data securely so that patient's profile will be created dynamically in the web portal. The cloud layer will also include necessary mobile APPs integration and live AV communication between patients and doctors. Through online remote connectivity, clinical instructors and rehabilitation therapists can guide patients on how to operate the system and/or initialise any initial parameters of the system. Cloud interface will also provide remote access for technical support and ensures security, system updates and maintenance. Through the web portal clinicians are able to view patients' health data and assess their progress. The system will allow doctors to select specific data and convert it into a portable format for secure electronic transfer of files to the hospital.

3 Conclusion

Currently, we are working in collaboration with the clinicians to develop a prototype system to evaluate the efficacy, usability and feasibility of the rehabilitation tool. After thorough evaluation of the system, the tele-neurorehab tool will be rolled out to the clinical trial phase once appropriate ethical approvals are being sought. Ethics play an important role in the application of tele-technologies to neurological conditions because several issues are associated with it, such as user privacy, accessibility, equity, social isolation, stress and mental and physical health [18]. Patient's empowerment should not be compromised while considering cost cutting through online tool. Relationships between clinicians, patients and family and/or carers can influence the rehabilitation process significantly. Therefore, ethical approval will be considered before starting any trials with human subjects, and informed consent will be taken from patients before the commence of clinical trial.

The proposed tele-neurorehabilitation tool can guide stroke patients assisting with the required exercises without the need for face-to-face interactions with the clinicians, especially during a pandemic. But the solution can be sustainable even after the pandemic is over as it cuts down cost for care considerably. The success of this tool depends on the assurance of privacy and security. The proposed framework ensures that the security measures are in place across all levels of the system (device, edge and cloud). Since the user's performance data will be stored in its secured internal memory and with all the secure protocol stacks installed, the framework will not be vulnerable to cyberattacks or network intrusions. The user interaction model will also integrate features such as online game-based therapy and group exercises to enhance patient engagement. By using the patients' performance data, a predictive model will be developed to guide the dose and duration of exercises, as well as estimate the recovery rate of patients. Implementation of the framework will significantly reduce the costs associated with post-stroke rehabilitation by allowing more patients to be supported by fewer staff with the help from AI-enabled software. In addition, using the tool clinicians can reach out to patients globally, especially to those living in low- and middle-income countries. And finally, use of the tool will reduce carbon footprints significantly by offering a full-service rehab to post-stroke patients entirely online.

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