Multimodal Data Streaming using Visual IoTs and Wearables for Telerehabilitation and Teletreatment

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***Abstract*—The current pandemic and the expansion of insurance coverage of telehealth for the elderly has shown the need for improvements in the automation of medical services and behavioral monitoring. Elderly individuals at home or in senior centers typically contact their physicians once a serious medical condition is obvious. There are very few systems with automated means of monitoring the health of individuals recovering from an injury or monitoring their progress when conducting telerehabilitation using wearables, remote cameras, and the cloud. To address these automation and long-term health monitoring issues, we have developed a multi-modal platform that employs common, low-cost wearables, and teleconferencing tools that takes advantage of cloud streaming services. One modality is based on Visual IoT and edge devices that automatically connect as teleconferencing clients to record human subjects' telerehabilitation and teletreatment sessions and push these recordings to cloud storage. We performed experiments applying two different deep learning models to the cloud video streams to track whole-body skeleton motion or to detect hand keypoints during telerehabilitation. The rehabilitation maybe associated with recovery from a stroke or other similar incident. The other modality of our platform includes an Apple Watch ® App that pushes users' physiological and kinematic data to the cloud and automatically generates data analytics dashboards for use by clinicians. Both, the wearables-based and the Visual IoT-based modalities complement each other in telerehabilitation or teletreatment controlled by clinicians. These modalities can also work together in sessions without the need for controlled (uncontrolled) telemonitoring. Our multi-modality, cloud-based architecture shows very promising applications in automatic behavioral analytics, especially for elderly individuals with limited social contact that would benefit from telerehabilitation, or continuous telemonitoring.**

***Index Terms*—wearables, visual IoT, teletreatment, telemonitoring, telerehabilitation, behavioral analytics**

I. Introduction

The remote monitoring and treatment of the elderly through vision devices and wearables, classified as Telehealth, Telemonitoring, and Tele-Treatment, have been growing rapidly in the last year largely due to the COVID-19 pandemic. One other reason for the growth is that insurance companies are increasingly covering telehealth services due to the expansion of the telehealth and virtual care services by the Centers for Medicare and Medicaid Services (CMS) in 2018 [1]. These practices are based on remote vision devices, e.g., cameras, and edge devices, e.g., micro computers, which combined are part of the Internet-of-Things (IoT). Their integration is referred to as Visual IoT's or VIoT's. Telerehabilitation is one area that leverages VIoT's to assist individuals during their physical therapy sessions. For example, individuals recovering from stroke need and benefit from routine telerehabilitation through video gaming and Augmented Reality (AR) [1] [2]. It should be noted that telerehabilitation often takes place reactively and the individuals' data are collected in a controlled way. That is, the treatment is controlled by clinicians and typically does not occur until a medical emergency takes place. So, there is usually sparse remote monitoring in weeks prior to or long after a medical intervention [3].

On the other hand, wearable devices can be programmed to monitor and collect physiological data continuously, automatically, and in a uncontrolled form. That is, clinicians do not need to manually control the health data collection, it is handled by the wearable automatically. For example, the Apple Watch® is a wearable that has gained tremendous usage recently and it has been reported to assist in detection of cardiac disorders through continuous and automatic monitoring [4] [5]. The drawback of the data from wearables is that by itself is not sufficiently accurate for a visual analysis by clinicians. So, there is a need to complement the wearables data with periodic, controlled vision data to provide a richer data stream as well.

To support this need, we propose a multimodal cloud-based data streaming platform that combines both controlled vision data collection utilizing VIoT's and uncontrolled physiological data collection using wearables. Our platform is scalable in that multiple VIoT's can be distributed in multiple locations with multiple users of wearables. Our platform captures both, the individuals' visual data and the physiological data. In addition, our system analyzes and visualizes the vision and wearables data automatically.

The rest of this paper is organized as follows: In section II, we include a condensed survey of related work. Section III illustrates the overview of our system architecture with details of the two components, namely the wearables and visual IoT components, expanded in Section III-A and III-B. Section IV and Section V describe the use cases of our architecture in telerehabilitation and teletreatment respectively. The experiments and the results for each of them are also mentioned in the corresponding sections. The conclusion of the paper is described in Section VI.

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II. Related Work

The concept of telerehabilitation introduced by Cooper, et al. in the early 2000's involves the application of remote sensing devices utilized to deliver medical rehabilitation at a distance [6]. Recently, there have been several VIoT-based applications for telerehabilitation as introduced by Cooper. One proposed system uses a VIoT composed of an RGB camera mounted above a sink to assist with handwashing in individuals with dementia. This system uses hand-tracking based on a Partially Observable Markov Decision Process and although it shows to be a fairly successful tracking method, the authors recommend additional sensor inputs to their model while the subjects perform the actions to improve tracking [7]. Another VIoT-based basic system was developed to automatically recommend therapies and two-way teleimmersion which is essentially teleconferencing between clinicians and individuals needing remote physical therapy [8]. This system follows the individuals' rehabilitation progress and also motivates the individuals as they routinely perform therapy sessions. In another VIoT-based telerehabilitation system, the authors showed improved skeleton-body tracking of subjects during in-home rehabilitation tasks using a constrained, extended Kalman filter algorithm and a low-cost RGB-D camera [9]. VIoT and computer vision have also been used in conjunction with deep learning models to determine the intensity of a human action [10]. In addition, a number of wearable-based teletreatment and telemonitoring systems have been proposed.

For example, one group presented a wearables-based system that to aid individuals suffering from Alzheimer's with face perception [11]. This uses a deep learning model embedded in a wearable to help identify people interacting with individuals with memory loss by reminding them of people they see regularly. Another platform was developed for recovery of limb functionality through inertial sensing modules attached to the limbs. This platform employed data fusion algorithms and cloud storage of the limbs' kinematics data for later review and analysis by physicians [12]. In another publication written by Dobkin, Rehabilitation Internet-of-Things or RIoT includes devices such as a smartphone interfaced with some type of wearable device interacting with the cloud. An App on the smartphone collects individuals' physiological data during rehabilitation and pushes these data to the cloud. Dobkin performed a low-cost, technology demonstration using triaxial accelerometers and gyroscopes attached to the ankles of his test subjects. With the aid of third party heart rate monitors, he studied the increase of self-managed rehab practices after individuals suffered a stroke; he also aimed to promote additional research and development of remote motor training [13]. As an improvement on VIoT-based or wearable-based platforms, multimodal platforms have been proposed [14].

Borresen, et al. designed one such multimodal platform that used color and depth cameras and a haptic device to provide force feedback over the internet from an individual at a remote location and a therapy clinic [15]. This platform was based on an Xbox® Kinect RGB-D camera, a haptic device, and

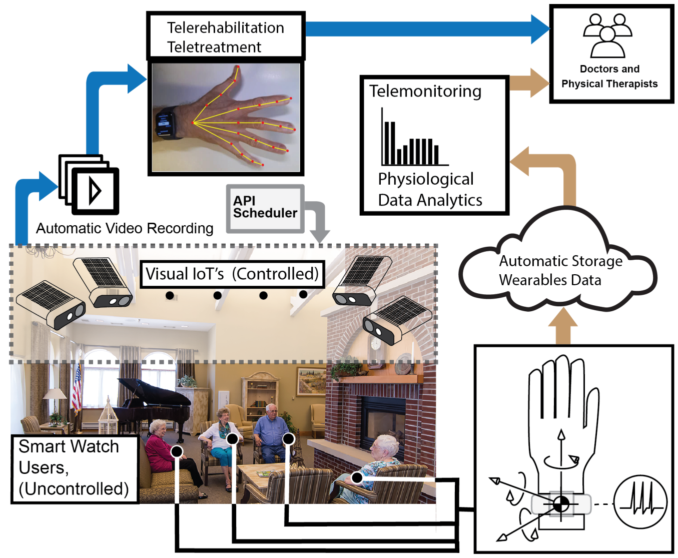


Fig. 1. Multimodal Edge Visual IoT and wearables platform. Brown data pathway: Wearables physiological data are continuously collected and pushed to cloud storage and data analytics dashboards for telemonitoring. Blue data pathway: On-demand video streams are stored in the cloud and AI hand keypoint or body tracking algorithms can be used to assist in teletreatment or telerehabilitation, simultaneously with data from wearables.

3D glasses at the therapist clinic and at the individual's home. The haptic device served to give the individuals going through the teletherapy session feedback on the amount of force being exerted during their exercises. Another multimodal platform was proposed to detect falls by elderly people living at home [16]. This architecture included an edge device interfaced with cameras on the walls of the individual's home, accelerometers and a heart sensor worn by the users. Predictions on falls by the elderly were based on image orientation, heart rate changes, and motion changes indicated by the accelerometers.

The literature suggests that existing multimodal systems are very limited in applications where vulnerable people are passively monitored on a regular basis or long after a medical procedure has taken place. Furthermore, most physiological wearables-based monitoring has been performed with specialized custom sensors or wristbands. Our proposed multimodal data streaming system has the advantage over previously proposed systems in that it is based on one a widely used smart watch and the physiological data it collects is seamlessly pushed to the cloud continuously. As it is described in the next section, these data are automatically visualized in a dashboard readily available to clinicians. In addition, our system integrates video recording capabilities through Visual IoT devices that can be used for teletherapy or teletreatment with the aid of computer vision.

III. Multimodal Data Streaming Architecture

Based on current literature, there is an evident need for significant improvements in long-term, automatic telemonitoring, and telerehabilitation/teletreatment in the health of vulnerable individuals, especially with a cloud-based framework. So, we designed our platform with the goal of automating the telemonitoring and teletreatment in a scalable, cloud-based, non-intrusive, and passive form. In particular, the use of off-the-shelf devices not only provides for a more open source path to development, the familiarity of these devices in the consumer market place likely can improve patient acceptance of these systems and lower the intrusiveness of the monitoring environment. As shown in Figure 1, this includes a dual modal data streaming ecosystem. One branch of our architecture is designed for controlled video data collection by clinicians utilizing multiple VIoT devices. The video RGB-D and audio data are acquired with a scalable number of VIoT's that behave as remote clients and are controlled via a server running an API scheduler program in an elastic cloud instance. Their RGB-D/audio data are pushed to the cloud automatically. The second component of our architecture runs without need for control or as an uncontrollable data collection system. This consists of a scalable number of smart watches (Apple Watch® series 6) pushing the users' physiological data to the cloud automatically. The smart watch's cloud data are uploaded to online data analytics dashboards periodically. Both of these modalities complement each other. That is, when the image data are not available, the clinicians can use the smart watch data to continue telemonitoring and likewise, use the video data to complement the smart watch data when the clinicians need to conduct more detailed image-dependent telerehabilitation or teletreatment. The way the two modalities function are described next.

A. Controlled Data Collection - Visual IoT

The controlled data collection is accomplished by our Visual IoT-based architecture. Our VIoT prototype includes six Microsoft® Kinects v4, each interfaced with a Zotac® E-series edge device and Graphics Processing Unit (GPU). We developed custom software based on the Zoom® Software Development Kit (SDK). Our software automatically schedules Zoom® cloud recordings triggering single or multiple Kinects with different fields of view. The schedule of the remote sessions is controlled by the clinicians or therapists treating the individuals. Our software is a server-client model designed to trigger one or more Kinects on demand. The edge devices connected to the Kinects behave as Zoom® web clients. The server runs indefinitely in a cloud instance and acts as a scheduler to invoke the clients at a time specified by end users (i.e. clinicians or therapists). An easy-to-use configuration file is maintained on the server to store client-related details like client id, Zoom® meeting link, meeting start time and meeting end time. The client invokes the server at regular intervals to fetch these details through a REpresentational State Transfer (REST) request and launches the Zoom® Web SDK application at the mentioned time. This modified web SDK allows us to automate the audio and video recording of the zoom meetings. Once the virtual meeting starts, the Kinect(s) begin recording until the end time defined in the scheduler is reached. The RGB videos are stored in the edge devices and the cloud and can be used in AI-assisted teletherapy.

1) Hand Keypoints Detection: Detailed hand keypoints' detection is an AI process that we can apply to the cloud video streams collected by our VIoT's. This can assist clinicians in teletherapy or telerehabilitation of individuals recovering from an injury or stroke. The model we chose for hand keypoint tracking is based on a modified version of Convolutional Pose Machines (CPM) and Multiview Bootstrapping [17] [18]. The neural network was created by researchers at Carnegie Mellon University (CMU) and was trained to track the motion of a human hand in RGB video recordings of images in the wild. The Deep Neural Network, DNN used in this model predicts a confidence map for each hand keypoint. These represent the coordinates of the keypoint as a Gaussian distribution centered at the true position. The final position of each keypoint is at the peak of the confidence map. The architecture of the DNN consists of a CPM that includes a Convolutional Neural Network (CNN) with a series of stages. We chose this model because of its relatively simple architecture based on ReLU activation functions and the model's efficiency at mitigating vanishing gradients. The loss function used in this model is based on the L2 or Euclidean norm with an added weight factor to discriminate against the undetected hand keypoints with missing annotations. The fundamental form of the model's loss function is:

$$J = \sum_{p=1}^{P+1} \sum_{x_p \in X} ||c_{true} - c_{predicted}||_2^2 \tag{1}$$

2) Body Keypoints Detection: Comparably to hand keypoints' detection, we can perform whole body skeleton keypoint/joint detection and tracking using AI models applied to the videos collected by our VIoT's. The skeleton tracking complements smart watch's physiological data in behavior and motion analytics conducted by tele-therapists. The model we used for skeleton tracking was the embedded model accessible through the Kinects' SDK. This model uses structured light imaging that incorporates a 2D imaging camera and a structured-light projector. Structured light imaging captures the three-dimensional topography of a surface using modulating patterns of light emitted by a projector and observed/captured by a 2D camera. A known pattern is projected onto a surface of an object, when the cameras see the pattern from different angles, the surface profile of the object distorts the pattern. The direction and size of the distortions are used to reconstruct the surface topography of the object or a depth map. From the depth map and RGB video frame for each video sample, the Kinects infer the body/skeleton posture using a randomized decision forest which is trained using a dataset with over one million images [19].

B. Uncontrolled Continuous Data Collection - Wearables

The wearable system of our platform includes a Swift App for the Apple Watch® series 6 and iPhone® iOS to record physiological data from sensors within the smart watch. These

TABLE I
PHYSIOLOGICAL AND KINEMATIC DATA CAPTURED WITH OUR APPLE WATCH® APP [20]

Data Recorded	Sensor Information	Range
Heart Rate	Green LED pulses, photodiode detector, photoplethysmographer	30-210 BPM
Blood Oxygen Saturation Level %	Green LED pulses, optical detector, oximeter	85-100 %
Noise exposure level	Microphone	30-120 dB
Resultant Acceleration Magnitude from front-to-back (x-axis), side-to-side (y-axis), and up-down (z-axis) components	6-axis Inertial Measurement Unit (IMU), 3 translational accelerometers and 3 rate Gyros. Gyro data not accessible through current Apple's API.	Translational accelerometers ±32 g's.

data are recorded and pushed to AWS® automatically. Our Apple® iOS Swift App is integrated with AWS IoT® via Amplify® iOS, which allows building native iOS applications powered by AWS®. The collected sensor data are transmitted to AWS® cloud in encrypted form and are stored in Amazon S3 (Simple Storage Service)® buckets. Amazon S3® is an object storage service that allows data security, availability, scalability, and performance. Every smart watch user's physiological data are uploaded as anonymously-labeled objects in S3® with a unique key, and body comprising of the incoming stream from the sensors and the corresponding timestamp.

The data stored in cloud is automatically updated, visualized, and analyzed in a Python web application as custom dashboards that are readily available to clinicians. The App can be easily reconfigured to record different sensor data from the smart watch at different sampling rates. In our current study, the App is programmed to acquire heart rate in beats per minute (BPM), blood oxygen saturation percent, noise exposure levels (decibels, dB), and three translational accelerations components (g's) which are part of the 6-axis Inertial Measurement Unit embedded in the watch. The resultant acceleration magnitude is calculated from these three components and this value is pushed to the cloud. The current configuration of our App is programmed to sample all the data every 10 seconds (0.1 Hz). However, the heart rate, blood oxygen data and noise exposure data update in the watch at intervals that are at least twice as long as our sampling intervals (i.e., lower frequencies). The accelerometers' response was evaluated against different sampling rates and the results are discussed later. Table I provides an overview of the data recorded and pushed to the cloud by our App.

IV. USECASE 1 - TELEREHABILITATION

Telerehabilitation consists of the "delivery of medical rehabilitation services at a distance using electronic information and communication technologies." [21] Similarly, Telemonitoring is defined as "the use of audio, video, and other telecommunications and electronic information processing technologies to monitor patient status at a distance." [22] Our architecture is capable of accomplishing the delivery and/or

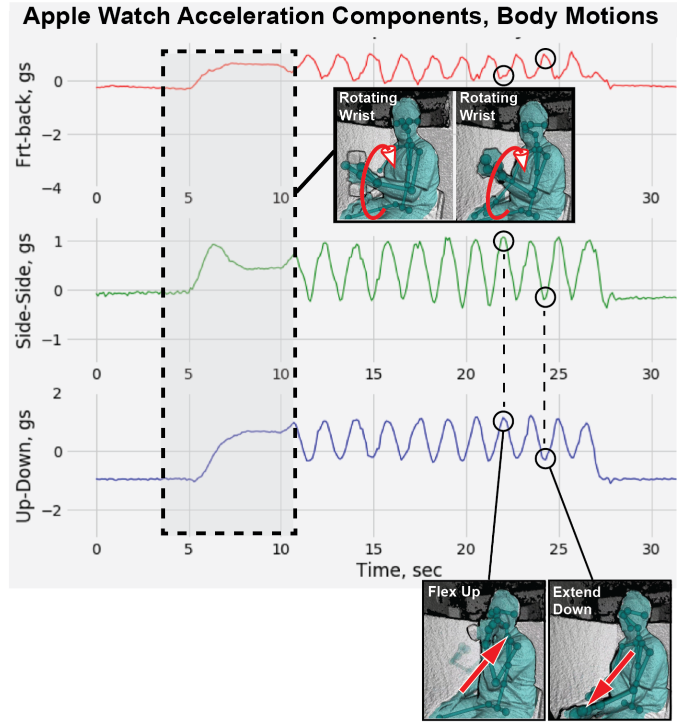


Fig. 2. Example experiment where translational accelerations were collected with smart watch and body/skeleton tracking was simultaneously detected in video recording. These data were retrieved from the cloud for visualization.

execution of either of the tele-services above to individuals at home or in a senior center with the cloud as the repository to all data streams. We focused the use of telerehabilitation on whole body therapy applied for example in recovery of an injury; and we also approached telerehabilitation on therapy for a portion of the human body such as the hand for example for individuals recovering from a stroke. The next two sections describe two examples of experiments in which we used our architecture to simultaneously collect videos, detect, and track specific body or hand keypoints while collecting kinematic data from the Inertial Measurement Unit (IMU) embedded in the user's Apple Watch® using our custom iOS App.

A. Full Body Rehabilitation

We performed experiments in which an individual conducted therapeutic exercises at home and his whole-body skeleton/joint tracking points were inferred from the RGB-D video data streams. The video streams were automatically pushed to cloud using Zoom® and the 32-joint body/skeleton tracking was performed accessing the model in the Kinect's SDK described earlier. The body tracking data was also pushed to the Elastic Search® cloud search engine through the use of Beats® and Logstash®. The experiments of this type were 10 minutes long and body tracking data was indexed in Elastic Search® within less than five minutes. The watch's IMU tri-axial accelerations were simultaneously pushed to an AWS S3® cloud storage within 10 minutes of performing the experiment. The smart watch's data depicted clear patterns of

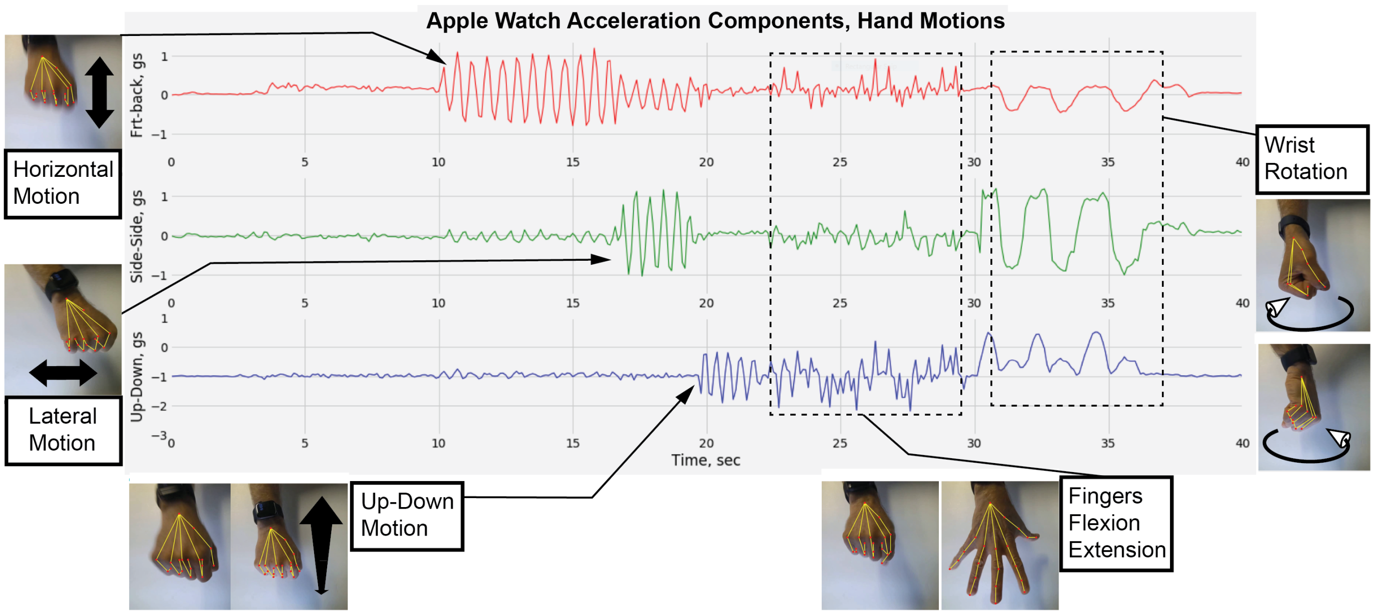


Fig. 3. Example experiment where translational accelerations were collected with smart watch and hand gestures were simultaneously detected in video recording. These data were retrieved from the cloud for visualization.

motion of the user that corresponded to the simultaneous body tracking data as shown in Figure 2.

B. Hand Rehabilitation

In a similar form as in whole-body rehabilitation, we performed experiments in which an individual conducted therapeutic hand exercises at home and his hand keypoints were detected in the color video streams by using the multi-view bootstrapping model described earlier. Similarly, the hand keypoints data were also pushed to the Elastic Search®. The corresponding Apple Watch® IMU tri-axial accelerations were simultaneously pushed to AWS®. As with whole-body motions, the smart watch's data depicted clear patterns of the user's hand motion corresponding to the hand keypoints tracked in the video streams. We observed that if severe occlusion of one or more fingers occurred, the model triangulated the location of the occluded fingers incorrectly and therefore possibly requiring an additional camera/view. If lighting and the Field-of-View (FOV) were properly adjusted, one camera was adequate for tracking the finger motions. An example of one of these experiments is shown in Figure 3.

V. Usecase 2 - Teletreatment

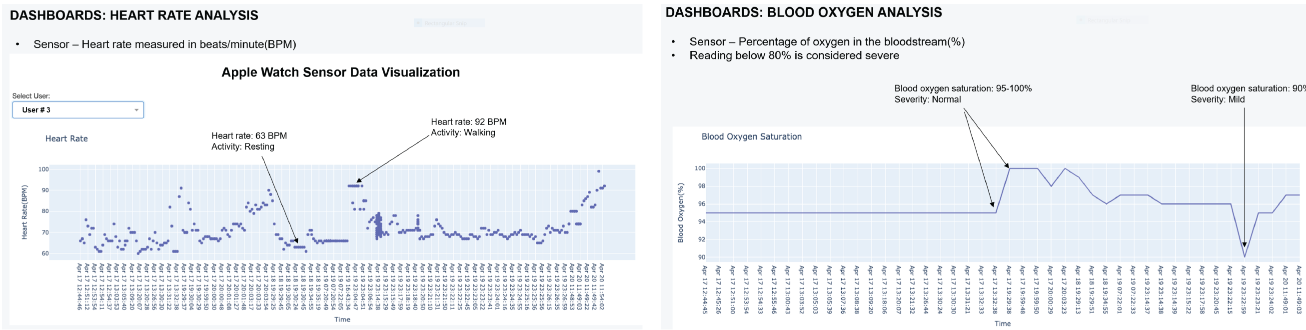
The concept of teletreatment has been described as "subjects equipped with a personalized interface consisting of a sensor system, which continuously measures relevant health functions and simultaneously provides the subject feedback on his functioning." These subjects are treated outside intramural care institutions [23].

We studied the feasibility of utilizing our architecture in teletreatment applications by collecting physiological data from two individuals for several days and analyzing these data in our custom dashboards. Their various activities were detected according to recommended thresholds [24]. However, these threshold values can be easily adjusted in the dashboards according to physicians' requirements.

Figure 4(a) describes an example dashboard for an individual's heart rate at rest and when active. Similarly, Figure 4(b) shows the blood oxygen saturation levels within which we identified the threshold values for mild and normal readings. The noise exposure levels were also detected such as when the individuals were listening to loud music (at or above 95 dB) or reading at a library (at or below 55 dB). We sampled the watch's translational accelerations at 100 Hz, 10 Hz, and 0.1 Hz. We determined that for tracking daily activities of the elderly at home such as moving, not moving, or moving rapidly, recording accelerations every 10 seconds was adequate. As noted in [10] [24], detection of other rapid motions require higher sampling rates. The maximum sampling rate in the current Apple Watch® is 500 Hz [20].

VI. Conclusion

We developed a multi-modality, cloud-based platform that includes a visual IoT-based system and a wearables-based system for controlled and continuous telerehabilitation and teletreatment. Our VIoT's system includes remote cameras and edge devices that automatically record the behavior of individuals conducting either whole-body or hand telerehabilitation routines after recovering from an injury or a stroke. In addition, our wearables system includes an Apple Watch® iOS App that automatically records and pushes users' physiological vitals and hand-wrist kinematic data to the cloud. The smart watch data are automatically visualized and analyzed in custom dashboards designed for clinicians involved in telemonitoring and teletreatment. We tested our VIoT system by scheduling



(a) (b)

Fig. 4. Example dashboards for (a) heart rate analysis and (b) blood oxygen saturation percent analysis.

automatic Zoom® sessions and recording common whole-body and hand therapeutic exercises while pushing the smart watch's kinematic data to AWS®. Two different deep-learning models were used to track skeleton joint movements or to detect keypoints in whole-body or hand motions collected in the cloud-based video streams. With our architecture, clinicians can review the tracking data of multiple sessions and assess the state of an individuals' rehabilitation over time. Encouraging results from our dual modality architecture indicate the effectiveness of the system to automate and improve long-term behavioral analytics for telerehabilitation and teletreatment, especially in elderly individuals at home.

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