VIRTUAL REALITY SYSTEM FOR REHABILITATION - CASE STUDY

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Abstract:

Nowadays, the number of patients with spinal pain is increasing. This paper presents research on a virtual reality system for patient rehabilitation with feedback during home exercise. The aim of the feasibility study of the proposed system was to analyze the accuracy of the exercise with tracking the patient's face and using the patient's avatar to provide the physician with an overview of the progress of the exercise quality. The virtual reality system will alert the physician in a timely manner if the patient experiences more pain during the home exercise. The use of the proposed system on a smaller sample of patients confirmed the hypothesis that patients with regular exercise experienced progressively less pain during exercise over a 4-week period.

Keywords:

Virtual reality, face tracking, HTC Vive Pro Eye, rehabilitation.

ACM Computing Classification System:

Virtual reality, Information visualization, Visual analytics.

Introduction

Virtual reality (VR) and augmented reality (AR) are promising platforms and technologies to support applications in areas such as healthcare. A head-mounted display (HMD) is a display device that is worn on the user's head in virtual reality. Techno-logical advancements in sensors, imaging techniques in HMDs, and their affordability have contributed to the increased interest in patient rehabilitation. VR has several advantages that can be used in rehabilitation: increased engagement in repetitive tasks, real-time monitoring of the patient's rehabilitation process, and interactions to enhance motor learning [1].

The rehabilitation program is carried out in a clinical setting under the supervision of a physiotherapist who continuously provides feedback on the correctness of exercises such as movement and posture to achieve the best outcome with effectiveness in both the short and long term. Feedback on the correctness of the exercise during or after performing the movement is very important as it promotes motor learning and its retention, thus minimizing possible side effects on health [2].

For proper feedback, it is necessary to ensure that the sensors are accurate enough to capture the movement. Vicon's precision motion sensing system is based on body tracking using markers on the body. Using the Vicon Tracker system, they tracked the limb movement of post-stroke patients in real-time using 15 markers tracked by 6 Vicon motion capture cameras [3]. Kinematic data of the participants were collected at a frequency of 120 Hz using the Vicon Tracker system. The overall results showed that avatar-based real-time feedback can be used as an intervention to improve gait asymmetry after stroke.

Leap Motion is another low-cost optical motion sensing device that is advantageous in upper limb rehabilitation programs to support natural interaction, where users' gestures and hand movements can be tracked with high accuracy. Another inexpensive motion-sensing device is Microsoft's Kinect, which incorporates depth cameras that allow full-body tracking without markers.

The study analyzed the impact of the motion system and compared it with results obtained from rules, templates, and clinical evaluation [4]. Doctors selected exactly five physical exercises for back pain. For each exercise, a set of data and functions were recorded that were specifically defined by the physicians and that described its scope. The system analyzed and compared the results obtained based on the defined rules from a large set of 78 subjects divided into 2 groups with 44 healthy subjects and 34 subjects with movement dysfunctions. This database allows the use of real-time control of the movement of the exercising person. For example, a dedicated software system 2Vita-B Physical for home rehabilitation was developed in Italy, which included motion tracking using Microsoft Azure Kinect [5]. The system was able to automatically assess the accuracy of the design of re-habilitation exercises. A preliminary study of rehabilitation plans achieved an average accuracy of over 85%.

The aim of the Horizon2020 project SenseCare was to develop a platform to analyze and visualize the data collected during the care of the elderly. Based on this platform, some rehabilitation-oriented applications were designed. In a prototype implementation, convolutional neural network methods were used to recognize psycho-somatic states while monitoring patients using Kinect, a microphone and a face-tracking camera [6].

Over the past 10 years, research on telerehabilitation technologies in post-stroke rehabilitation has developed rapidly [7]. Both the technology base and the improved quality of research have demonstrated that the efficacy of telerehabilitation is superior or equivalent to traditional rehabilitation methods, but new approaches still need to be found. Another study reviewed publications according to the methodological quality of physiotherapy evidence databases and showed that, compared with conventional rehabilitation, telerehabilitation using VR has comparable outcomes in upper limb function and balance in patients after stroke [8].

In this section, we discuss the use of immersive VR in rehabilitation. The global immersive reality (iVR) market, which includes augmented and mixed reality in addition to virtual reality, was worth $29.3 billion in 2022 and is expected to grow to over $100 billion by 2026 [9]. In iVR virtual environments that use mirroring of the exerciser's movements, a virtual proxy of the exerciser needs to be visualized. The role of avatars in iVR environments is to mediate the persons perception, identification, representation and visualization of actions. In the case of iVRs with eye and facial expression tracking sensors, the avatar can additionally display the emotions of the users, which can be used to identify negative or positive emotions of the persons during the exercise. In many studies, the DeepFace algorithm has been used for face recognition and trained on more than four million images of identified facial emotions [10]. In interpersonal communication, facial expression is one of the most important information channels, so in our study we also followed the evaluation by similar algorithms using 6 basic types of emotions according to Eckman.

Immersive stimuli using iVR are the key to influencing user-body behavior because they have the ability to provide a sense of presence and engage emotions in the virtual-world [11]. The potential benefits of acting on a person's feedback using their avatar-ra open up new possibilities for rehabilitation [12].

The study extensively searched publications focusing on VR applications in exercise and concluded that iVR in conjunction with stimuli and biofeedback is a new area that is under-researched [13]. An interesting study investigated intensity ratings of different emotions in iVR [14]. Participants in the study tried several iVR games and reported their emotional experiences in a questionnaire. The analysis confirmed intense responses in several emotion components. The analysis supported the hypothesis of the multi-component nature of the elicited emotions and grouped them into differentiated patterns, with fear and joy being the most strongly represented emotions as in Eckman's study.

Rehabilitation programs in VR have many advantages because they create greater presence, better control over the exercise, and engagement of the practitioner. Our research and clinical studies have highlighted various innovative uses of VR in healthcare, with one of the interesting applications of VR being emotion detection in nano-arthroscopic surgery [15]. The proposed VR Training with Avatar program followed a movement activity mainly focused on training adepts using emotion tracking.

1 Materials and Methods

In this section, we describe the equipment used to apply the training system, the selection of subjects to test the exercise recording, and the overall design of the Training program. An important part of the system is tracking the eyes and face of the subject in order to evaluate the emotions experienced by the patient as pain.

1.1 Technological equipment

To test the hypothesis of the effect of VR rehabilitation on reducing spinal pain, it was preferable to use the HTC Vive Pro Eye along with the Facial Tracker device, which provides better information to assess the patient's emotions and a more realistic exercise environment, although it requires a more challenging technical environment. The HTC Vive Pro Eye provided a resolution of 2880 × 1600 (1440 × 1600 pixels per eye). The required hardware configuration was implemented based on the available HW in our laboratory. The software solution is also optimized for use with other types of HMDs supporting eye or face tracking (Oculus Quest2 and Meta). We used high-performance computers with a Core i9 processor, 32 GB of RAM and NVidia RTX 2070 graphics card, 1 TB SSD. For rehabilitation of patients at home, we rented them high-performance laptops with Intel Core i5 12500H processor, 32 GB DDR5 RAM, NVIDIA GeForce RTX 3060 6 GB graphics card, 1 TB SSD.

HTC Trackers were used to track a person's upper and lower limbs, and body. The HTC Tracker is a device that is used to extend the virtual reality capabilities of the HTC Vive. Its main purpose is to track physical objects in the real world and transfer their movement into virtual space. HTC Trackers have been paired with the HTC Vive system and transmitted their movement data to Steam VR and further to the Unity development environment. The HTC Vive device itself provided enough data to reconstruct a good full-body avatar in the apps. Motion tracking accuracy in such a setup ranged from 1 to 2 millimeters.

1.2 Sensor-based avatar animation

For sick patients, wearing many sensors would be uncomfortable and could restrict movements, which is undesirable in a rehabilitation application. To reduce the number of sensors, we do not track every movement or rotation of every bone and joint. Instead, we only track the position and rotation of a specific part of the body, called the end effector, i.e., the head, arms and legs, and waist area. To determine the position and rotation of the remaining body parts, we have to solve the problem using inverse kinematics. After calculating the position and rotation of the remaining (unmeasured) body parts, these values are set as the positions and rotations of the avatar in VR. This computation is done in real time, thus ensuring the animation of the avatar in the virtual reality environment.

The skeletal data (i.e., the trajectory of the positions and orientations of the virtual joints) is computed post-power by a modified algorithm proposed in [10]. Sufficient trained intelligence is stored in the system to analyze what it sees and evaluate it with the stored collection of skeletal structures to interpret the movements. The avatar information is anonymized person data and therefore can be stored in a database of patient skeletal movements with eye movements and facial gestures according to defined values as data for exercise analysis in the cloud.

By having the physician or rehab worker download this information about a particular patient from the exercise database, they can link the patient's actual physique, face, and eyes on computer, what allowing them to better monitor and evaluate the selected patient during the exercise who previously saw at the rehab facility. In (Fig.1) we see an example of an HTC Vive with a device to track a person's face and their avatar.

HTC VIVE Pro Eye in HMD generates various data related to eye gestures. We used the EyeDataManager class from the SRanipal wizard [16] to extract eye gesture data and in a study on creating avatars from sensed data [17]. The maximum sampling rate of the eye tracker was 120 Hz, based on which we processed the extracted data. We processed the received data and then extracted eye data related to openness, pupil size, blinking, eye position, expression, and gaze target.

(**a**) (**b**)

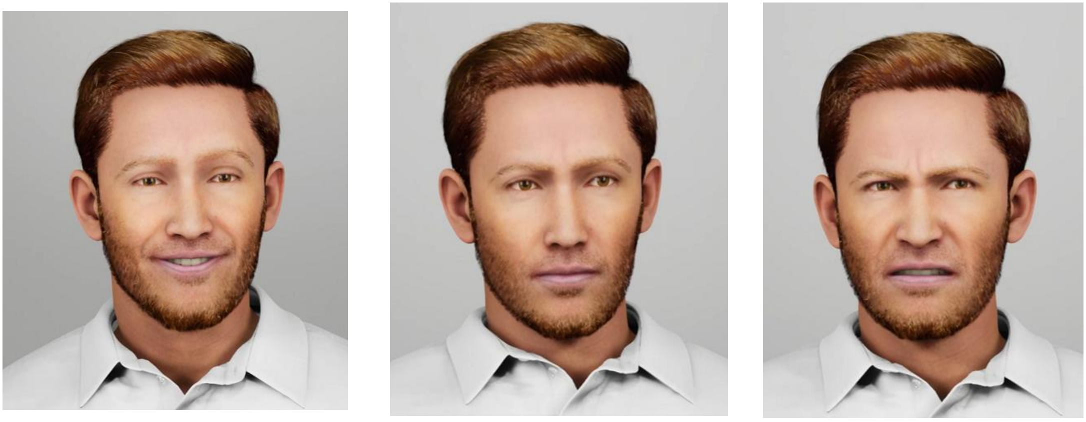
Fig.1. This image shows facial expressions: (a) capturing facial expressions with the HTC VIVE Pro Eye and Facial tracker; (b) MetaHuman avatar showing captured emotions.

The VIVE Facial Tracker was connected to the HTC VIVE Pro Eye using a USB-C cable. We used the FacialDataManager class to capture data from the sensor, following the same steps as for eye sensing. The Facial Tracker API captured data according to a defined sampling rate of 120 Hz. The received data contained 38 data items related to jaw, mouth, tongue, face, and sensor status. A more detailed description of the eye and face tracking signals using the HTC VIVE is given in the Vive SRanipal Unreal SDK manual [16] and similarly as given in reference [17].

Based on the data captured from the human eyes and face also transferred to the avatar, we defined neutral, positive, and negative states similarly to the study in [15]. (Fig.2) shows 3 facial emotional states, the first one corresponding to joy and the other two to neutral and negative expressions according to Eckman's basic emotions.

1.3 Selection of persons and exercises

We selected five exercises commonly used in rehabilitation programs for spinal pain. The procedure was modified to exclude VR patients who have vision problems (too strong diopters, strong squinting, problems with 3D perception in VR) or dizziness (vertigo, loss of balance from high altitude, inner ear or vestibular nerve disease). A VRSQ value of less than 9 is recommended for VR use. The VRSQ questionnaire presented here comes from a study [15] with VRSQ values ranging from 0 to 27. In designing our system and exercise database, we followed a similar procedure as in that study [4] and recruited 5 healthy control patients (HC), 6 post-stroke stroke patients (STR), and 4 Parkinson's disease (PD) patients to test the system. The initial phase was conducted in a rehabilitation facility for 6 days to ensure that each patient became sufficiently familiar with the HTC device, even with the help of a family member. After 6 days, the physician assessed the patient's condition, and the therapist evaluated the person's experience with VR. (Tab.1) shows basic information about the patients such as gender, age, height, VRSQ score at the beginning of the exercise, and VR experience after 6 days in the rehabilitation facility.



(**a**) (**b**) (c)

Fig.2. This figure shows facial expressions using Eckman's representation: (a) positive emotion; (b) neutral emotion; (c) negative emotion.

Table 1. Basic parameters of selected patients for VR rehabilitation (STR - stroke, PD - Parkinson's disease, M - Male, F - Female).

N.	**Patient**	**M - F**	**VRSQ**	**Age**	**Height in cm**	**VR exp.**
1	STR	M	7	68	168	7
2	STR	M	2	39	170	3
3	STR	F	3	44	165	4
4	STR	M	2	37	180	2
5	STR	M	3	41	178	2
6	STR	F	4	62	169	3
7	PD	M	3	50	179	3
8	PD	M	5	55	155	3
9	PD	F	4	56	163	5
10	PD	F	5	67	159	7

We also used data from the KIMORE database and designated exercises as Ex1 to Ex5 [4]. The designed rehabilitation exercise system allowed the physician and therapist to make evaluations of the exercises. We designed exercise quality in a way that searched from defined skeletal exercise points during the course measured from the average from the HC group in selected positions, for example, at the beginning and at four to eight phases of one exercise cycle.

From the deviation from both the skeletal points and the end angles marked as in the KIMORE database, we calculated the exercise quality of each exercise Ex1 to Ex5. A brief description of each exercise Ex1 - Ex5 from publication [4]:

- Ex1: Lifting arms
- Ex2: Lateral tilt of the trunk with the arms in extension
- Ex3: Trunk rotation
- Ex4: Pelvis rotations on the transverse plane
- Ex5: Squatting.

1.4 Initial exercise phase and accuracy assessment

The patient exercise procedure in the Training system was designed with the help of doctors and rehabilitation staff of Rehamed Piestany. Each exercise was repeated 5 to 25 times, with 3 breaths in and 3 breaths out between each exercise Ex1 to Ex5. After the five exercises Ex1 to Ex5, the doctor suggested two short stretching exercises, which were part of the rehabilitation, so that the total time did not exceed 15 minutes. The speed of the exercises and the number of repetitions at home were determined by the physician individually for each patient. After one cycle of exercise, a short 0.5s break was always taken as a time reserve for possible delays in home exercise. The initial phase took place in the rehabilitation facility 6 days, during which 10 patients trained using VR Training system. After the first initiation week, patients were asked to exercise at home in the VR system for at least 2 weeks. After two weeks, a one-day review of the exercises was conducted at the facility to repeat the acquired stereotype and to check exercise accuracy with the physiotherapist.

Training System was prepared with the help of the 5 therapists so that their average movement during a single exercise at certain time intervals determined the basic framework for assessing the exercise accuracy of the patients. The height of the exerciser determined the normalized skeletal points for comparison. For each ExK exercise, one time cycle and a certain number of intermediate IK phases were determined according to the exercise K (e.g., for Ex1, 4-time intervals were taken for the full arm lift and their skeletal points (j) were converted to normalized height). For 6 days, the data set of normalized skeleton points at given time intervals (i) of phases was determined as ExK_HC(i,j) for the average of healthy (HC) according to their height for ExK. For each patient N on the ExK exercise on a given day, we can determine the error rate (FR) according to the difference from the normalized healthy dataset, which we denote by FR(K, N).

$$FR(K,N) = \sum_{i=1}^{IK} \sum_{j=1}^{Scelet} Distance(\mathrm{ExK}(i,j,N), \mathrm{ExK\_HC(i,j)}) \qquad (1)$$

In order to have a normalized scale for graphical display, we determined absolute values for ExK. We defined the maximum failure rate (AbsFR) for all ExKs and all patients. This value was given by the relation:

$$MaxFR = Max\ (FR(K,N)),\ pre\ N = 1,..,10\ a\ K = 1,..,5. \qquad (2)$$

The absolute error rate (AbsFR) for exercise K and patient N is given by the percentage error rate of the exercise to twice the maximum normalized error rate.

$$AbsFR\ (K,N) = FR(K,N)/(2*MaxFR). \qquad (3)$$

(Tab.2) shows the mean values with standard deviations for VRSQ, age, height and absolute error rate AbsFR(K, N) of exercise K for healthy and diseased subjects. The above table shows that in our sample of healthy and sick subjects, the absolute error rate was lowest for the first exercise Ex1 and highest for the third exercise Ex4.

Table 2. Averages for age, height and AbsFR for exercise.

	Age	Height	Ex1	Ex2	Ex3	Ex4	Ex5
Average of therapists	35	172	2.1%	3.5%	4.1%	3.6%	3.9%
Average of patients	55	165	45.3%	48.5%	51.7%	52.8%	51.7%

2 Designed Training System

In this section, we describe the main features that are built into the Training System: pre-practice and save exercise, demonstration of correct exercise, the exercise itself with feedback, tracking the patient after the exercise at home offline, and tracking the patient at home online. (Fig.3) below shows a diagram of the above functions and modules. The system was also implemented for MS HoloLens, in which the patient was displayed to the physician using a hologram.

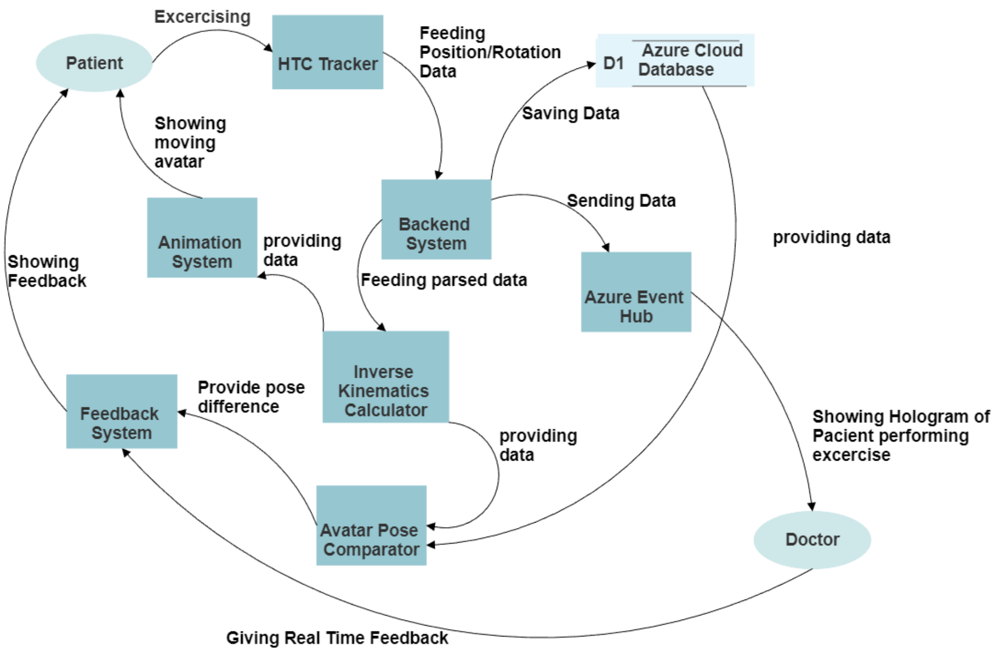


Fig.3. Diagram of the main functions of the Training system

2.1 Preparation and recording of the exercise

The application is divided into modules for recording exercises and the exercises themselves. The recording of the exercises is done by the physiotherapist according to a template selected and designed by the physician. The pro-process consists of practicing one repetitive exercise, which is saved as a template to be practiced by the patient. This pre-practiced exercise is then available to the patient in the exercise app. The exercises are stored in json format in the Azure cloud in the Blob storage. (Fig.4) below shows a physiotherapist practicing the lifting arms exercise (Ex1).

2.2 Exercise module

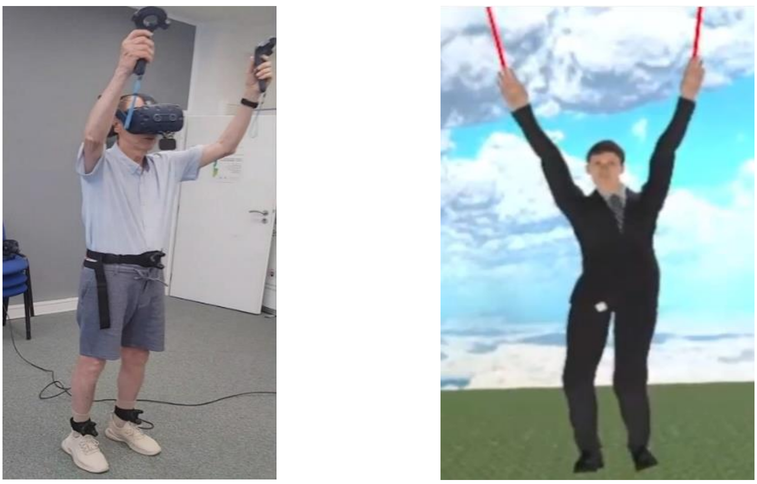
In Exercise module, the patient can see how to perform a specific exercise. After selecting this module and the selected ExK exercise, the avatar of the physiotherapist appears next to the patient's avatar in the virtual reality.

After one cycle of the physiotherapist's exercise, the patient repeats the exercise according to the physiotherapist to maintain the selected rhythm and accuracy of the exercise.

(a) (b)

Fig.4. Create template for Lifting arms exercise:
(a) physiotherapist performing the exercise; (b) view in the Training system.

During incorrect exercises, the patient receives feedback via red arrows that are placed at limb. If the position or rotation does not significantly match the physiotherapist's exercise, then a red arrow is dynamically displayed in the direction of the change in movement. (Fig.5) shows a patient performing the lifting arms exercise. The red arrows at the end of the arms indicate that the patient should lift the arms higher.



(a) (b)

Fig.5. The picture shows the patient during lifting arms exercise Ex1:
(a) as he lifts his arms during the exercise; (b) as an avatar in the Training system.

2.3 Offline patient monitoring

Patient performance is sampled every 0.1 seconds and all necessary information is stored in the operating memory in the background. When the patient completes an exercise, this exercise is transferred in json format to the Azure cloud to the Blob storage and stored using a unique GUID. This identifier is paired with the patient's account. It is the only link between the patient and their exercise data from which the patient's unique identity cannot be determined. This allows an anonymous playback of the patient's exercises using an avatar that shows the patient during the exercise, thus allowing the physician to analyze the patient's performance during the exercise.

2.4 Online patient monitoring

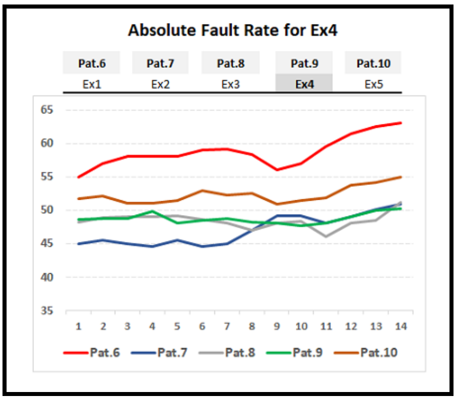
The application enables real-time transmission of exercises to a remote device. This feature allows the patient to be monitored as a virtual reality avatar during exercise at any distance and provides the ability to provide instant voice feedback to the patient during rehabilitation.

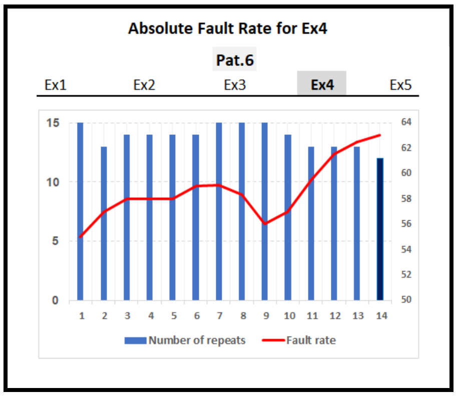
3 Results of the Case Study

In this section, we present the results of the visualization and analysis of the evaluation of the training system for monitoring patients exercising at home. The summaries presented were intended for physicians and physiotherapists. We divided them into 4 parts: exercise accuracy analysis, facial monitoring analysis, pain analysis, and questionnaire analysis.

3.1 Exercise accuracy analysis

The physician and physiotherapist could get a quick overview of how the exercise had evolved in the last days. The training system allows to view different summary visualizations of the patients' exercises over time, down to a detailed view of the patient for a given exercise in weeks. The visualization is similar to systems using Business Intelligence. For example, after selecting multiple patients Pat.6, Pat.7 to Pat.10 during an exercise, a graph of the AbsFR error values by selected exercise Ex4 was displayed (Fig.6a), and after selecting patient Pat.6, for example, additional information about the number of repetitions of the exercise was displayed (Fig.6b).





(a) (b)

Fig.6. a) Visualization of AbsFR for Ex4 exercise of selected patients Pat.6 to Pat.10 over 14 days; b) the blue bars are the repetitions for Ex4 exercise of patient Pat.6 and the red line is his AbsFR error rate.

For exercise assessment, the training system allowed the physician and physiotherapist to monitor longer time intervals ranging from 2 to 8 weeks. This allowed patients' exercise performance to be monitored and compared and any errors to be identified even over longer time intervals.

3.2 Face tracking analysis

We tracked the movement of both eyes at 120 Hz while the patient was exercising using the HTC Vive Pro Eye. We counted the number of saccades at the edge of the projected portion in the HMD similarly to the study [15]. To assess emotion, we recorded the number of eye movements at the edge of the projected portion in the HMD for 25 ms. Similarly, we tracked facial emotions determined using the Facial Tracker attachment at 120 Hz.

We experimentally verified negative emotions and finally determined the following algorithm. We considered negative emotions when the eyes were withdrawn for 1 second, or when the eyes moved rapidly (saccade) within half a second outside the edge of the projected part, or when the patient's gaze remained 2 seconds outside the view of the avatar in the HMD, in which case we assigned only half the value of the negative emotion. In addition, we determined the negative facial emotion from a selection of faces determined by the Facial Tracker device from the 38 defined from the SRapinal Facial Tracker manual [16], which were aggregated and evaluated together with the emotions from the eyes when necessary.

For graphical display purposes, we normalized the data by exercise duration. We adjusted the time interval to 20 units (as for the average exercise duration) and transformed the maximum number of normalized emotions for the patient to 10 units. For each patient N on an ExK exercise on a given day, we can determine the number of negated emotions (Emo) during his or her ExK exercise, which we denote Emo(K, n), during the retention time Itime that we determined for each exercise.

$$Emo(K,N,day) = \sum_{i=1}^{Itime} \mathrm{Emo(K,N,day,i)} \tag{4}$$

To have a normalized scale for graphical display, we determined the absolute ExK values during exercise from the first 6 days. We defined the measure of negative emotion during ExK exercise as the percentage of emotion that is twice the maximum normalized value calculated from the initiation phase of 6 days of exercise in the rehabilitation facility:

$$Emo(K,N) = \sum_{day=1}^{6} Emo\,(K,N,day) \tag{5}$$

$$MaxEmo(K) = Max(Emo(K,N), for\ N = 6,\ldots,10. \tag{6}$$

We defined the emotion measure for exercise ExK and for patient N on a given day from calculations (4) and (6):

$$EmoRate(K,N,day) = Emo(K,N,day)/\,(2 * MaxEmo(K)) \tag{7}$$

The results also show, on a smaller sample of patients, how appropriate visualization can be selected for rapid analysis of patients. (Fig.7) shows the data in normalized emotional values from the eye and face for patient 6 during the pelvic rotation exercise in the transverse plane (Ex4 exercise).

3.3 Pain analysis

Through the facial tracking features in the system, the values of the morphological shapes of the avatar can be animated by moving mainly the lips of the person, as described in the SRanipal manual [16]. The avatar of a person has 38 shapes defined corresponding to face and lip tracking. Of these morphological avatar faces, the closest approximation to pain is the squinting of one eye and the simultaneous lifting of the right or upper lip towards the squinted eye or the simultaneous lifting of the lips with the squinted eyes. The recorded values were summarized for a single exercise with a frequency of 0.1 seconds. Figure 8 shows the basic avatar corresponding to the pain from SRapinal.

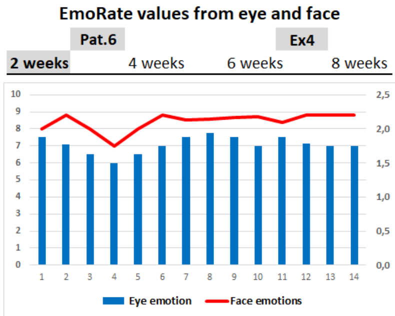


Fig.7. EmoRate values from the eye and face for patient Pat.6 during Ex4 exercise.

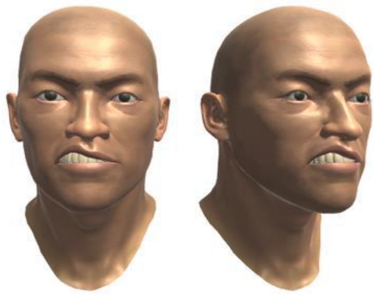


Fig.8. Avatar face with upper lip raised from the SRapinal Unreal SDK guide (Mouth_Upper_UpRight and Mouth_Upper_UpLeft) matching the experience of pain.

The clinician could view a video of each day's exercise of the selected patient offline, which was displayed as an avatar (see Fig.9). An alarm signal was prepared in the exercise database to alert the physician if the patient significantly exceeded the tolerable error threshold compared to the mean (i.e., FR(K, n)/MaxFR>0.7). In such a case, the physician could immediately review the patient's video recording offline and, in case of obvious deficiencies, discontinue the home exercise or call the patient for a follow-up examination.

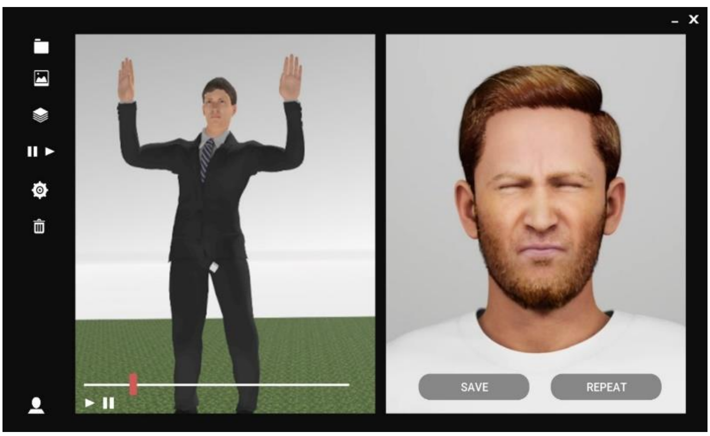


Fig.9. Video of a patient showing him as an avatar during the exercise: (a) the video can be paused; (b) the corresponding detail face of the patient avatar at that moment.

(Fig.10) shows the mean pain values recorded in patients by group (STR and PD) during exercise using facial tracking, the x-axis is the time axis for 24 days and the y-axis is for the normalized pain values. The R2 value shows how closely the estimated values of the trend line fit the actual data. In our case, for stroke patients R2 =0.9448 and for Parkinson's patients R2 =0.8771, which is a very good fit to the data.

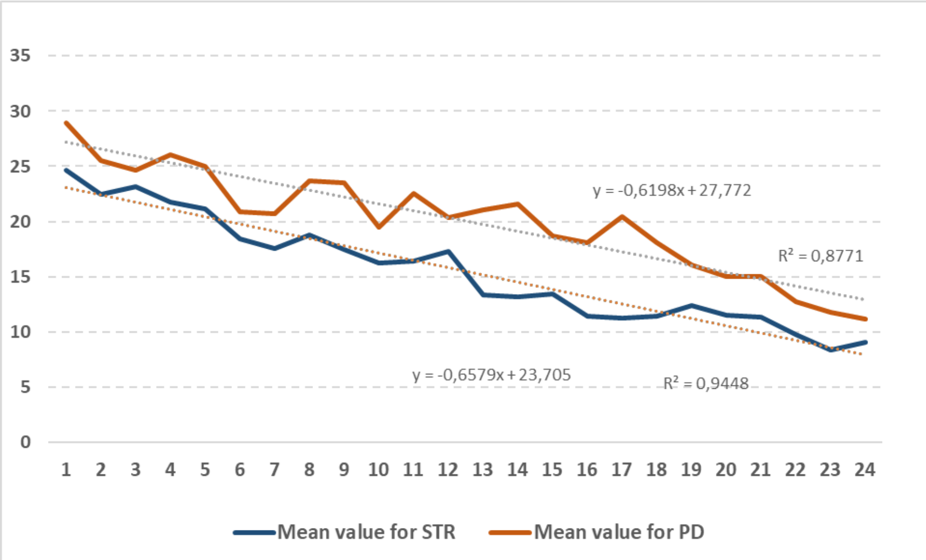


Fig.10. Line graph of mean pain in patients over 4 weeks (24 days) with a linear trend. The blue line shows the mean pain values in patients after stroke and the red line shows the mean pain values in patients with Parkinson's disease.

4 Discussion

According to the results to date and a review of publications from the IEEE, PubMed and SCOPUS databases, this is the first case study that enables rehabilitation in a home setting using anonymized cloud-based data logging with face tracking. The training system allows online or offline exercise tracking using the patient's avatar and anonymized face, providing the physician with a quick overview of the patient's exercise quality progress and timely post-exercise alerts to the physician if the patient experiences significant pain during exercise. Comparison of the pain monitoring results from the face in Section 3.2 (Fig.10) showed a correlation between the different conditions and also a gradual reduction in pain during exercise. If more patients undergo VR rehabilitation at home according to the proposed scenario, we plan to investigate this study in detail using the statistical methods described in the publication [18].

These results suggest that pain assessment in post-stroke patients also had a positive impact on treatment in terms of pain survival. Similar findings were also reached in a previous project focusing on exercise for post-stroke patients using VR games [19]. The aforementioned method of pain sensing using facial monitoring allows patients' pain to be objectified and can be used in other virtual reality exercises and tested to monitor patients during exercise.

In a study, a system was designed to monitor post-stroke patients without a therapist present using a color feedback system in which patients could self-correct their exercise during exercise [20].

Instructions on the degree of difference in joint orientation between the patient and the template were generated from Kinect or camera images, which could be used to create a skeleton of the patient. A drawback of the system was that it did not support the uploading of patient videos due to GDPR privacy concerns. Our training system displays an anonymized patient using their avatar (see Fig.9).

Our findings confirmed that patients exercised at home with more breaks than in the rehabilitation facility and switched between real and virtual worlds between exercises, similar to the study reported in [21]. On average, exercise accuracy at home deteriorated over time, and therefore exercise monitoring at the rehabilitation facility should be repeated after 2 to 3 weeks on an individual basis depending on the patient.

When using immersive VR in people with spinal pain, it is important to monitor them after exercise and make sure that the rehabilitation is being performed accurately enough as instructed by the physiotherapist. Therefore, it is good when the clinician has the ability to monitor appropriate summary information about the rehabilitation during home exercise using visualization and can draw conclusions from offline assessment of patients. Future research needs to expand the list of different types of exercises to include as wide a range of limb and whole-body exercises as possible, and also to establish more detailed correlations for a sufficient number of patients.

Conclusion

The implementation of our Training system has been done in such a way that it can be adapted to new prospective VR devices that will be developed in the future. A standardized technical specification for training implementations has not yet been widely adopted, and existing implementations rely primarily on proprietary technologies. An important avenue for further research will be to investigate in detail how adaptation to altered movement-sensory environments in a rehabilitation facility affects exercise at home, and what kind of virtual home environment is best for each individual patient, in which artificial intelligence may also play an important role.

Acknowledgement

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