Diagnosis and Rehabilitation of Motor Learning Difficulties using Virtual Reality

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Abstract
Diagnosis of motor learning difficulties refers to the identification of motor difficulty and rehabilitation means the ways of restoring to its default function. This paper explains how virtual reality can be innovatively integrated to perform this process effectively by leveraging machine learning. Identifying one's motor learning difficulties often requires evaluation by an expert. Rehabilitating one motor problems also requires supervision. The paper explains the methodology of automating the task of identification and rehabilitation of motor learning difficulty. Results and findings from an early experiment suggest how this process can be integrated into the healthcare system in conjunction with the traditional methods. It also explains the consistency, reliability, and accuracy of this newly developed technology. The ultimate aim of this research paper is to propose a new paradigm shift in the way we diagnose and rehabilitate people with motor learning difficulties.

Keywords
Assistive technology; Virtual reality; Machine learning; Rehabilitation

I. Introduction

Virtual Reality (VR) is defined as an interactive computer-generated experience taking place within a simulated environment. While VR is primarily used for gaming and entertainment, we instead focus on therapeutic purposes. Virtual reality therapy (VRT) is the use of VR technology for physiotherapy or occupational therapy. My research is focused on patients with motor skill disorders such as dyspraxia, dysgraphia, and visual perceptual disorder and their rehabilitation of upper-limb. While many VR therapies are focused on only rehabilitation
of the patients, I instead focus on both diagnosis and rehabilitation. Standardized assessment is the most common form of diagnosis practiced. Patients are manually assessed by making them perform a certain task while the psychologist evaluates the patient's movement and behavior.

My research is focused on automating this task so that the patient can perform self-diagnosis without doctor intervention. By observing the hands poses, behavior, and dexterity, we can classify different motor skill disorder in the upper-limb of the patients using machine learning. After that, the patient can perform VR exercises to rehabilitate. I carefully analyze the improvement and progress of the patients. My research also compares the efficacy of virtual rehabilitation with traditional rehabilitation.

My dissertation includes: measuring and classifying meaningful hand gestures, poses, and behavior; developing a machine learning model to identify the motor ailment; designing virtual reality games to rehabilitate the ailment, and measuring the effectiveness of the virtual rehabilitation.

II. Methods

A. Evaluating hand gestures and poses

Our hands are composed of 27 bones each. Each one has its specific function in the formation of the structure of the hand. The primary motor cortex, or M1, is one of the principal brain areas involved in hand motor function. The role of the primary motor cortex is to generate neural impulses that control the execution of hand movement.

The neurological disorder in this part of the brain can trigger a motor learning difficulty often referred to as dyspraxia. Individuals with dyspraxia have difficulties in planning and completing fine and gross motor tasks. A diagnosis of dyspraxia is carried by a clinical psychologist, an educational psychologist, a pediatrician, or a therapist.

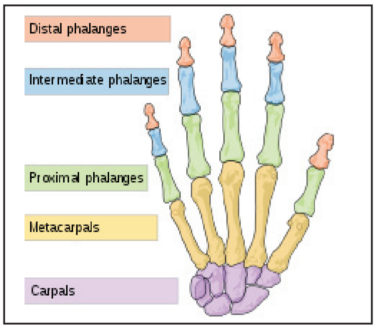

Fig. 2:

My approach is to automate this diagnosis process so that patients can perform self-diagnosis without the presence of the doctor. I do this by tracking each segment of the hand using oculus hand tracking technology. Oculus hand-tracking allows me to retrieve the information about each bone; like position, rotation, behavior, and dexterity. The hand information is retrieved by engaging the patient in a series of hand exercise VR games like color matching, shapes sorting, etc. After the session, we can extrapolate various features of the hand using my proprietary algorithm.

This extrapolated data also gives valuable information about mobility, bilateral hand co-ordination hand-eye coordination, and quality of movement of the patient which are very important while training our classification model. The data is extrapolated at 60 frames a sec and is exported in CSV file which is later used in the classification of the difficulty. The settings of the application also can be tweaked; like the sensitivity, difficulty, time limit and speed aligning with the patient's preferences. It can reduce the false-positives and false-negatives that is generated after the classification is done.

Fig. 3:

B. Classification of motor learning difficulties

Therapists perform assessment tests like wolf motor function, fugl mayer assessment, Brunnustars movement theory to determine what kind of difficulties is the patient suffering from. For example, in the fugl meyer assessment test, the evaluator evaluates various locomotory organs and joints in the body. Observing the patients and assigning a test score to their task in a piece of paper is a common approach to all these assessments. Test scores manifest whether the patient has poor balance, poor posture, poor integration of the two sides of the body, poor hand-eye coordination, etc. The evaluator finally concludes the motor learning difficulty the patient is suffering from.

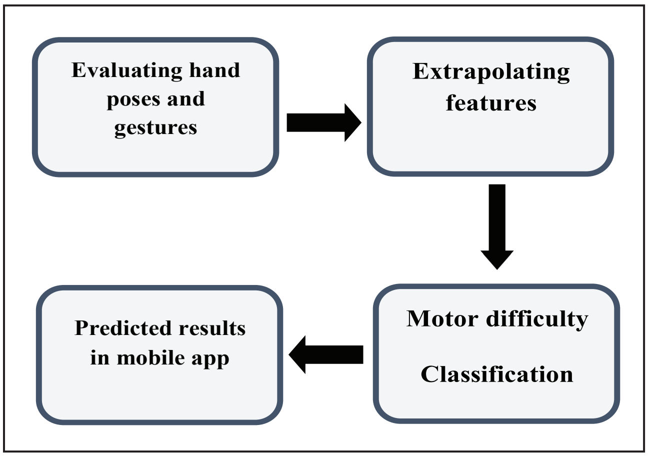

Fig. 4:

My approach is also similar but instead of the therapist, we use machine learning to determine motor difficulties. From the extrapolated data retrieved from the previous session, my model can identify the symptoms of the patient suffering from motor learning difficulties. I do this by training the retrieved data with neural network regression using azure machine learning studio. It can dynamically pick the bests type of regression (linear, logistic, polynomial, etc.) and if not accurate enough, I can add hidden neuron layers to make the model more complex and improve its prediction power. The trained model predicts how likely a patient suffers from the following motor difficulty. It predicts the value from 0 to 100. This process is done by establishing a connection of my Unity app to the ML studio API through a rest-client. The data retrieved and extrapolated from the hand tracking is fed to the endpoint URL. The machine learning model runs in the cloud and it provides the predicted results in JSON format. The JSON is parsed and visualized in a line graph in our mobile app. Exercise with a score of 5 is considered excellent and a score of 1 is very poor. For now, I am using synthetic data for training purposes. I am still in the process of collecting data from patients in psychology centers, therapy centers to increase the model prediction actuary.

C. Designing Rehabilitative Game

After rehabilitation, patients gain only 15 % pf their motor ability because of no follow-up rehab program. To tackle this problem, I have designed virtual environments where the patient can regain their motor control by playing games in a cheap and accessible Virtual reality. The games range from catching a fast-moving ball, throwing the ball, sorting the colored ball in the colored basket, etc. These games are designed in such a way that patient is immersed in the virtual environment and feel like they are playing in a real life. The game is designed in such a way that it only presents you with the task that you have the most difficulty in. For example, if you have difficulty in catching a ball because of the limited range of volar flexion and dorsal flexion, it presents you with a game where you have to catch the ball. My game automatically identifies the type of motor difficulty you are suffering from the previous diagnosis step and presents you with the task accordingly. It also automatically adjusts the difficulty based on patient progress and improvement. It is designed in such a way to enhance the patient's balance, posture, and hand-eye coordination. I am particularly focused on upper-limb rehabilitation so the games are primarily for hands and fingers. It is designed in such a way that it promotes cognitive and physical cohesiveness. It restructures the wiring of the brain and improves the neural impulse picked up by the motor organs.

III. Results and Findings

To test the results of our application, we organized a workshop in collaboration with the Orthoplast rehab centers. We recruited 10 patients and divided them into a group of two. The first group consisted of 3 males and 2 females (n=5) with a mean age of 18.4 years. (σ = 1.3). The second group consisted of 2 males and 3 females (n=5) with a mean age of 27.5 years (σ = 3.6).

Group	Traditional Diagnosis (Wolf-motor function test)	
First	**Task**	**Score**
	1. Upper Extremity	40/66
	2. Lower Extremity	28/34
	3. Sensory Function	20/24
	4. Balance	12/14
	5. Joint range of motion	38/44
	6. Joint pain	36/44
	Total	**174/226**
	Performance Rate – 76.99%	
Second	**Task**	**Score**
	1. Upper Extremity	38/66
	2. Lower Extremity	28/34
	3. Sensory Function	16/24
	4. Balance	10/14
	5. Joint range of motion	30/44
	6. Joint pain	30/44
	Total	**152/226**
	Performance Rate – 67.15%	

Group	Virtual Diagnosis	
First	**Task**	**Score**
	1. Dorsal Flexion	4/5
	2. Volar Flexion	3/5
	3. Radial Abduction	4/5
	4. Ulnar Abduction	2/5
	5. Hand eye co-ordination	4/5
	6. Fine motor skills	3/5
	Total	**20/30**

	Task	Score
Second	1. Dorsal Flexion	1/5
	2. Volar Flexion	2/5
	3. Radial Abduction	3/5
	4. Ulnar Abduction	3/5
	5. Hand eye co-ordination	2/5
	6. Fine motor skills	3/5
	Total	**14/30**
	Performance Rate – 46.66%	

A. Accuracy of Diagnosis

Wolf-motor function is regarded as the standard assessment test. The performance rate for the first group doing virtual diagnosis is 66.66% while the performance rate of the group doing traditional diagnosis is 76.99%. It means that the accuracy rate of virtual diagnosis is 86.5 %. Again, the performance rate for the first group doing virtual diagnosis is 46.66% while the performance rate of the group doing traditional diagnosis is 67.25%. It

B. Efficacy of Virtual Rehabilitation

Traditional rehabilitation refers to the use of physical objects and equipment to rehabilitate. The same group participated in a week-long virtual session. They were instructed to use virtual rehabilitation and traditional rehabilitation for 30 mins each for a week. After 1 week, the participants in both the group were evaluated again.

Group	Virtual Evaluation	Traditional Evaluation
First	Performance Rate 74.66%	Performance Rate 86.66%
Second	Performance Rate 56.66%	Performance Rate 75.66%

In both cases, there was a slight improvement in the performance rate of the participants. On Average, the performance increased by 10%. This improvement is only after 1 week of the session. If the participants used it for longer, then we may have seen more improvement in the performance rate.

IV. Conclusion

The error rate from virtual diagnosis is comparable with the error rate of the ML model. The approach to designing the ML model is correct. The virtual diagnosis was also successful in evaluating the patient's motor movements with an accuracy rate of 70%. It was successful in evaluating the first group but failed in evaluating the second group. The virtual rehabilitation was also somewhat effective in the development of the motor skills of the participants. The table elucidates a 10% increase in the performance rate in both after virtual evaluation and traditional evaluation. Hence, the results from this experiment deduce that virtual reality has the potential to be used in the diagnosis and rehabilitation of the motor learning difficulty.

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Avinash Gyawali is currently pursuing his higher education in GEMS Instiute of higher education located at Kathmandu Nepal.He had been awarded as the finalist of Microsoft imagine cup for the impact that he had created using virtual reality. He has also been awarded as NASA Space apps winner for his contribution to NASA.