Nanotechnology Perceptions
ISSN 1660-6795
www.nano-ntp.com

Enhancement Of Finger State Progress Model for Markerless Virtual Fine Motor Stroke Rehabilitation

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The use of machine learning as a tool for analyzing and pattern extraction from the results is widely applied in various medical applications in stroke rehabilitation. It will help the therapist to make a consistent and precise evaluation for a viable recommendation for an optimal future exercise to improve the patient's progress. The objective of this study is to produce a prediction model to analyze patient finger rehabilitation progress by comparing four regression classifiers' efficiency. In this study, we proposed an Enhancement of the Finger State Progress (E-FSP) model to produce prediction results of progress and performance which also consists of a markerless VR application using markerless motion sensors and can capture kinematic data through Time-based Simplified Denavit Heartenberg (TSDH) model and measure the results of rehabilitation exercises through the integration of Finger State Progress (FSP) model. 30 patients have undergone rehabilitation sessions using VR applications in the Kuala Nerus Rehabilitation and Hemodialysis Health Organization. The study shows the result of an optimum evaluation is the RandomForest classifier which has the lowest Mean Absolute Error (MAE) value of 8.26 and Root Mean Square Error (RMSE) value of 12.38. In conclusion, The VR application and machine learning can produce a very promising combination of attractive visual and viable prediction analysis for virtual fine motor stroke rehabilitation.

Keywords: Evaluating Regression, Fine Motor Rehabilitation, MAE, Virtual Reality.

1. Introduction

The stroke attack is very impactful to patients physically and emotionally. The burden of stroke is very significant to the patients, families, and societies if the patients have long-term disabilities [1]. Rehabilitation should commence as quickly as possible and intensively to reduce disabilities [2]. Therapists have a vital function in the recovery of mobility-affected stroke patients. It will take an accurate analysis by the therapist to ensure the ideal report, which can be a problem for the therapist when he needs to supervise many patients to fulfill rehabilitation procedures. The lack of therapist accessibility during exercise sessions, as the therapist needs to handle many patients simultaneously for an ongoing exercise appointment slot, will make the performed exercise in-comprehensive and unutilized timewise [2].

A consistent analysis is also an issue if the assessment is manual and varied according to the therapist's experience. Accurate assessment patterns of rehabilitation outcomes in diagnosis and decision on therapy are very important [3] to the therapist. A lot of benefits can be gained, such as reduced healthcare costs and complications [4]. The therapist can also utilize the advancement of sensors and machine learning algorithms to help them monitor home-based rehabilitation [2]. By using traditional methods, it becomes very difficult to extract meaningful information from it. However, it is now possible to extract meaningful patterns from it due to advancements in the fields of statistics, mathematics, and every other discipline. The integration of machine learning in rehabilitation analysis or application is very helpful. Many research in recent years embrace this integration in their study or application [1], [3], [5], [6], [7].

A stroke rehabilitation therapist can use VR as a complementary method to achieve better results in post-stroke rehabilitation and ease the healthcare service burden [8]. The results of virtual therapy may be enhanced by differing variables such as the repetition, duration, period, and precision of the therapy [9]. Although the use of virtual environments (VE) is growing in popularity in this research field, the number of research studies performed in VE is still limited, especially in terms of the upper and lower limbs [10].

In this paper, we propose an E-FSP model for virtual fine motor stroke rehabilitation progress and performance, and a new dataset has also been presented. This paper is organized as follows. In section II, the proposed framework and datasets that will be used for evaluation processes are discussed. In Section III, the evaluation results are presented. Finally, our work in this paper is summarized in the last section.

2. Proposed evaluation model

Three exercises have been designed which cover the basic finger movements in VR application and use a Leap Motion Controller (LMC) [11]. After each exercise, stroke patients will be instructed to accomplish the maximum finger grasp and extension movement. The framework consists of three phases; capturing finger movement by using TSDH [12], measuring finger data by using the FSP [13] model, and finally, the Enhancement of Finger State Progress (E-FSP) model for progress and performance evaluation.

2.1 Capturing and Measuring Finger Kinematic Data

There is initial 2 datasets captured with TSDH, a dataset of 30 stroke patients' finger movement, and a dataset of a benchmark movement for fingers’ grasp, rest, and extension from healthy person fingers. For the initial measuring of finger performance, the FSP model has been used to calculate movement progress by using Linear Regression to be projected on the virtual application UI. Then, a detailed evaluation of finger progress will be processed by the proposed model.

2.2 Enhancement Finger State Progress (E-FSP) model

Good It consists of a regression evaluation process of the dataset by comparing with four regression classifiers; Linear Regression, SMOReg, Multilayer Perceptron (MCP), and RandomForest classifier with a 10-fold cross-validation evaluation technique. All four regression evaluations also will be processed by applying Feature Selection to be compared to the result of the full attributes. A correlations-based feature selection was used to assess the correlations by using CfsSubsetEval [14-18].

The efficiency of evaluation results is determined by the lowest value of Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) which will measure the average extent of the errors. Mean Absolute Error is the mean of the sum of absolute value for all error values between the predicted value and with actual value. All error values will be positive. It will indicate the error range for result prediction [19-25]. Root Mean Squared Error is the square root of the mean of the sum of the squared error value between the predicted value and with actual value [26-29]. The size of the error value will directly impact any outliers and can amplify the value of the results greatly if there are any outliers in the dataset.

Datasets: The collected data from TSDH will produce 2 datasets (Dataset 1 and Dataset 2) which will through several processes and will be combined to form the final dataset (Dataset 5).

Table 1. Details of Datasets

Dataset	Details	Instances
Dataset 1	Normal/Healthy Finger state of Grasp, Rest, and Extension dataset	61
Dataset 2	Stroke Patients dataset from VR rehabilitation exercises.	4172
Dataset 3	30 Stroke Patients dataset evaluated with SMOReg classifier	60
Dataset 4	30 Stroke Patients dataset evaluated by Expert (Goal attribute value will be replaced by expert assessment)	60
Dataset 5	Combination of Dataset 1 and Dataset 4.	121

Table 1 shows details of the datasets involved in the E-FSP model. Each dataset contains 28 predictor attributes and 1 goal attribute. Dataset 1 and Dataset 2 were monitored by the therapist when the capturing process happened and went through data preprocessing.

Dataset 1 is a dataset constructed with the data of a normal or healthy person of finger state for grasp, rest, and extension position. Dataset 2 is a dataset of stroke patients' exercise data from the rehabilitation exercise on data collection sessions. Dataset 3 is the result of stroke patients' rehabilitation exercise data (Dataset 2) which is processed with a SMOReg classifier to find the maximum patient finger movement for grasp and extension. The SMOReg classifier is chosen to process Dataset 2 because it is the most optimum classifier for Dataset 1 based on regression comparison results. Dataset 4 is Dataset 3 evaluated by the therapist. The Dataset 3 data will be translated into a graph of maximum patient progress of grasp and extension, which consists of two graphs for each patient in a total of 60 graphs (30 patients x 2 data for each patient (maximum and minimum progress)). The objective of Dataset 4 is to generate a dataset that contains the therapist-evaluated score.

Dataset 5 is a combination of Dataset 1 and Dataset 4. The aim of Dataset 5 is to produce a dataset that contains the data of a healthy person's finger movement, and the therapist evaluated patients' data. The final objective of Dataset 5 will be used to be a prediction model for future evaluation of finger progress and performance for a stroke patient's rehabilitation session.

Evaluation Model: Figure 1 show the datasets and the E-FSP process flow. It is to produce the datasets and finally to evaluate the final dataset (Dataset 5) with selected regression classifiers in searching for the most efficient regression classifier to be used for Dataset 5. A total of five datasets have been involved. Dataset 1 goes through the process of finding the lowest MAE and RMSE values with the selected regression classifier. This process will go through cross-validation. The dataset will be divided into two sets; one with full attributes and the other one with selected attributes based on feature selection. The regression classifier from this process with the lowest MAE and RMSE value is labeled as Result 1. Dataset 2 is created by capturing stroke patients' rehabilitation sessions.

Next, Dataset 1 is used as train data, Dataset 2 is used as test data, and Result 1 is used as a regression classifier to generate progress value on Dataset 2. Then, a maximum and a minimum progress value for each patient are selected and packaged into Dataset 3. Dataset 3 contains 60 data. Based on data on Dataset 3, 60 graphs were constructed.

Next, the 60 graphs are evaluated by the therapist. The therapist will assess the graph and will value the patients' progress with their own experience. Dataset 4 is constructed by the combination of Dataset 3 with the assessment result by the therapist. Dataset 4 will go through a cross-validation process. The dataset be will divided into two sets; one with full attributes and the other one with selected attributes based on feature selection. The regression classifier from this process with the lowest MAE and RMSE value is labeled as Result 2. This process evaluates the consistency of the therapist's assessment for each data for Dataset 3 before.

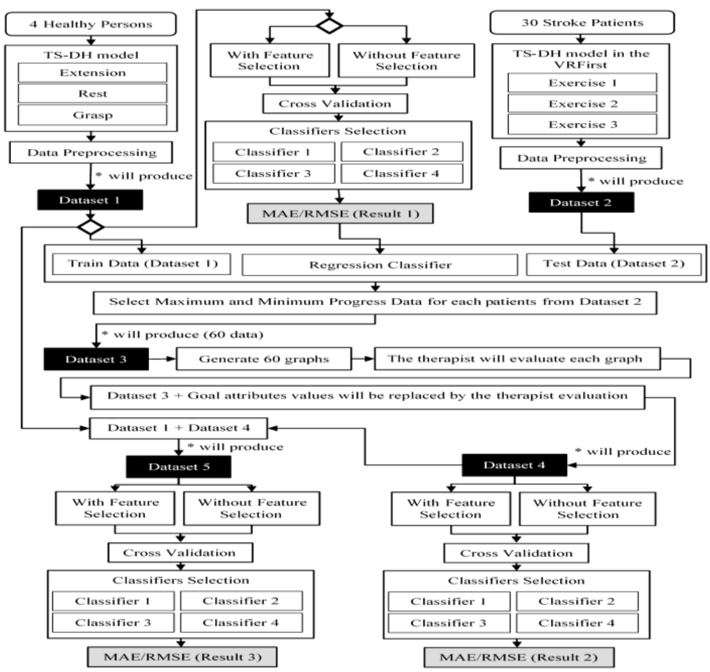

Figure 1. The Datasets and E-FSP Processes

Finally, Dataset 1 and Dataset 4 are combined to establish Dataset 5. Dataset 5 will go through cross-validation. The dataset be will divided into two sets; one with full attributes and the other one with selected attributes based on feature selection. The regression classifier from this process with the lowest MAE and RMSE value is labeled as Result 3 which is the final result to be chosen as the most efficient regression classifier for Dataset 5.

3. Result and discussion

3.1 Healthy Person Data

A session was conducted to capture the finger movement of four persons consisting of three positions and evaluated on the regression classifiers. Finger movement is grouped by three measurements: 0 for a grasp, 50 for a rest, and 100 for an extension. Then, two parameters will be used; joint angle and joint length then the joint translation will be produced by the TS-DH model. The joint translation will be processed by the E-FSP model which will be evaluated by using four Regression classifiers to determine which classifier is more fitting to be used as patient progression analysis.

Table 2. Four Regression Classifier Evaluation for Four Healthy Persons (Result 1)

Classifier	With Feature Selection		Without Feature Selection	
	MAE	RMSE	MAE	RMSE
Linear Regression	10.7075	15.3397	16.5712	22.4093
MLP	13.6315	18.7641	8.8484	13.8893
SMOReg	10.119	15.461	6.3021	11.2204
RandomForest	9.8197	17.9194	9.7049	17.9194

Table 2 shows four Regression Classifier Evaluations for four (4) Healthy Persons consisting of three-finger movements (extension, rest, and grasp). The evaluation shows that the SMOReg classifier without Feature Selection has the lowest MAE value between Linear Regression, Multilayer Perceptron, and Random Forest.

This result will be used to assess collected patient data (Dataset 2) to specify the maximum and minimum of patient finger movement. Since the finger movement is categorized into 100 for extension and 0 for grasp, the regression result can be normalized into a percentage value, where the nearest value to 100 will be spotted as maximum progress for extension and the nearest value to 0 will be spotted as the maximum value for grasp.

3.2 Patients Data

The result from Table 3 which is the SMOReg classifier, will be used to process patients' data. As a result, a new dataset (Dataset 3) with 60 finger movement data was selected where each patient would have 2 data; the maximum movement for extension and maximum movement for grasp.

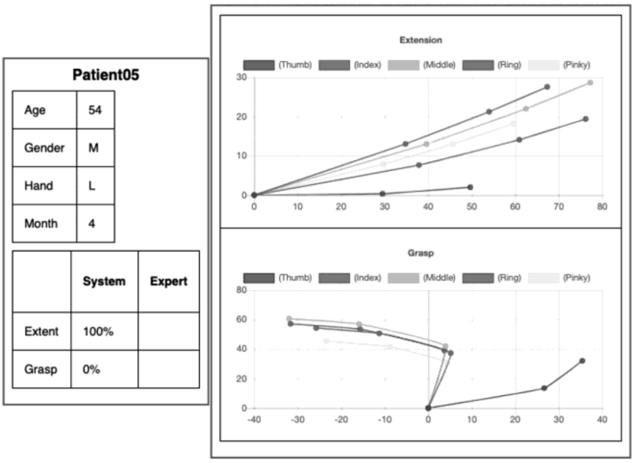

Figure 2. Expert Evaluation Form

Figure II shows an example of one of the patient data by using the result from Dataset 3 to find the maximum for extension and grasp. The therapist will mark it in the 'Expert' column. A session was conducted with a stroke therapist to assess the patient's finger progress based on patient data that was processed by SMOReg regression to identify the maximum and minimum of finger movement during rehabilitation exercise. Each patient will have two graphs categorized into extension and grasp progress. A total of 60 graphs based on Figure 2 were produced for 30 patients. A new result based on a therapist assessment is made to be processed and compared in four regression classifiers. The result used only therapist assessment in progress (Goal Attributes) value.

Table 3. Four Regression Classifier Evaluation for 30 Patients with Expert Assessment Result (Result 2)

Classifier	With Feature Selection		Without Feature Selection	
	MAE	RMSE	MAE	RMSE
Linear Regression	7.4404	9.1625	7.2788	9.1307
MLP	5.847	7.8594	7.5319	10.1355
SMOReg	7.1404	8.8304	7.3044	9.4927
RandomForest	6.0198	8.6496	4.82	7.2434

Table 3 shows the result of the comparison by using four regression classifiers for 30 patients' data that were assessed by only a therapist (Dataset 4). The result shows that the RandomForest classifier without Feature Selection has a lower MAE than other classifiers. This means the consistency of therapist evaluation for patient progress data is more or less 4.82% as the score is normalized into the percentage.

3.3The Final Dataset

For the final process, Dataset 1 and Dataset 4 will be combined and used to finalize a regression evaluation.

Table 4. Four Regressions Classifier Evaluation for Healthy and Evaluated Patient Data Combined (Result 3)

Classifier	With Feature Selection		Without Feature Selection	
	MAE	RMSE	MAE	RMSE
Linear Regression	9.5103	12.8572	9.9503	13.4752
MLP	11.1212	14.4657	10.4214	16.056
SMOReg	8.956	13.2148	8.3494	12.4373
RandomForest	9.6302	14.659	8.2632	12.3839

Table 4 shows a result of comparison by FSP for a healthy person and the therapist evaluated the patient's data. RandomForest classifier without Feature Selection results shows that it has the lowest MAE compared to the other three classifiers. It also shows the RMSE result is the lowest.

It can be concluded the RandomForest without Feature Selection is the optimum regression classifier for Dataset 5 to be used as a patient's progress evaluation for fine motor stroke rehabilitation.

4. Conclusion

An evaluation model and a new dataset for virtual fine motor stroke rehabilitation have been designed and proposed in this study. In this framework, the optimum pre-diction process to evaluate finger progress by using the proposed model Enhancement Finger State Progress (E-FSP) is presented. This result can be used for the prediction of fine motor stroke rehabilitation performance to produce an analysis for particular session reporting or as a comprehensive comparison of rehabilitation results between different sessions. In the future, large-scale data on finger progress can be collected and analyzed to produce a more precise assessment to be used as a standard evaluation of finger movement progress for stroke patients.

Declaration

Funding	Supported in part by the e-Science Fund by MESTECC, UniSZA Virtual Reality(VR) grant
Conflicts of Interest	No conflicts of interest to the best of my knowledge.
Ethical Approval and Consent of Participate	UniSZA Human Research Ethics Committee (UHREC) ref:UniSZA.C/2/UHREC/628-2(38).
Availability Data and Material	Not relevant
Authors Contributions	All authors have equal contributions to this article.

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