Finger State Progress Model for Virtual Fine Motor Stroke Rehabilitation

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ABSTRACT
Manual observation in measuring and assessing stroke patient progress in fine motor rehabilitation will lead to inconsistencies especially when the patient is evaluated by different therapists or attends different rehabilitation facilities. In addition, it also increases therapist workload if they need to supervise many patients at the same time. Thus, a model was proposed to capture finger data from motion sensor device using Time-Based Simplified Denavit-Heartenberg (TS-DH) and the Finger State progress (FSP) model. Actual finger movement was compared with patterns of finger state for real-time evaluation of finger movement progress. The model will assist therapists in real-time or post-exercise evaluation of patient progress and analysis can be done during stroke rehabilitation exercise. As a conclusion, the model can be used efficiently in virtual stroke rehabilitation as real-time indicator or as a long term analysis to compare prior progress.

Keywords: *Leap Motion, Linear Regression, Stroke Rehabilitation, Virtual Fine Motor.*

I. INTRODUCTION

Stroke rehabilitation is crucial for stroke patients to ensure the impact on lasting sensory and motor impairment is lessened. Rehabilitation is conducted by a therapist who will monitor and analyze a patient's condition manually in each session in order to plan and prepare appropriate exercise based on the patient's progress. It will take a very precise analysis by the therapist to produce an ideal report which can pose a problem to the therapist when he needs to supervise many patients to fulfill rehabilitation procedures [1]. Fine motor is the most affected motor skills in stroke attack which makes activities of daily life (ADL) of the patient more difficult. The disabilities with the highest impact for the patient are hand function and upper limb weakness. Nearly 90% of stroke patients will have a long-lasting effect and will not recover their upper extremity function after impairment of upper limb [2].

With increasing amount of stroke patients, the therapist can only provide minimal hours of rehabilitation sessions using the current traditional method [3]. Many patients will have to wait to be slotted into rehabilitation schedules. The therapist evaluation of rehabilitation performance is also subjective to therapist assessment [1] and may differ from clinic to clinic [4]. The therapist will also be exhausted in the process which involves many procedures and needs to tolerate patient broken condition physically and emotionally. The situation worsens by a lack of accurate analysis in rehabilitation performance using the manual method [5].

Traditional method of collecting fine motor rehabilitation progress such as manual observation using goniometer will need a single therapist to particularly observe one patient at a time. It is a challenge to accurately measure the patient's finger movement and determine if there is any improvement. By using motion capture technology and statistical analysis which has seen a lot of progress, data can be mined efficiently. Data mining method is very useful when large set of healthcare data are obtainable [6], [7] through the process of capturing data in virtual reality application.

Data mining is a proven method and is widely used as an analysis tool in various fields such as medical analysis, industrial design, marketing analysis, fraud discovery, and mass media predictions [8]. Data mining will also increase the chance of early discovery [6], the quality of healthcare assessment decision making [9],[10], connections between healthcare data [11] and patterns [12], improve accuracy [13] and also significantly reduce the cost of medical treatment [6],[11].

By providing computerized measurement with data mining method, it will assist the therapist to monitor and evaluate patients' fine motor rehabilitation improvement with minimal supervision and effectively produce a variety of progress report.

This paper is organized as follows. In section 2, the research framework is provided. Section 3 discusses the comparison between internal device coordination with TS-DH and processing the captured finger data for 3 states of finger. In Section 4, the proposed framework for measuring rehabilitation progress and performance will be discussed. The experimental results of calculation using FSP model by using finger coordinate is presented in section 5. Finally, our work in this paper is summarized in the last section

II. VIRTUAL FINE MOTOR STROKE REHABILITATION FRAMEWORK

A VR application integrated with robust framework paired with markerless motion sensor has been designed and developed in this study in order to recognize stroke patients and therapist perspective of the VR technology usage as fine motor rehabilitation tool for stroke for analyzing finger movement progress and performance through rehabilitation exercises [15].

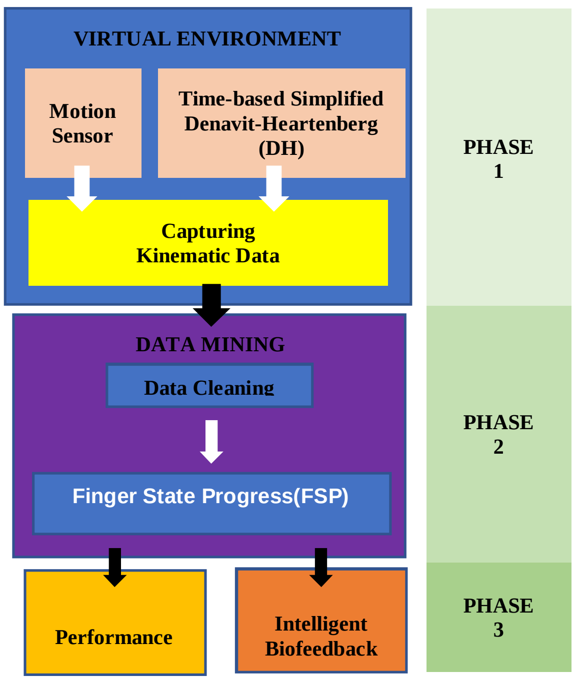

Fig.1: Virtual Fine Motor Stroke Rehabilitation Framework

Figure 1 shows the framework that had been used for rehabilitation progress of fine motor for stroke patients. The framework is divided into three phases.

The first phase is capturing finger kinematic data by using motion capture device. Virtual finger bones is generated based on motion capture reading. All joint angles is recorded into a database during rehabilitation session. Time-based Simplified Denavit-Heartenberg (TS-DH) technique is used to produce a steady time-series coordinate result for each finger joint based on every finger bone angle [13]. The second phase is measuring the progress by using Finger State Progress (FSP) which will be discussed in this paper. A coordinate calculation from TS-DH technique is cleaned and grouped into Seconds. Data reference of finger progress measurement is produced and grouped in grasp, rest and extension state of fingers by researcher. For FSP, the data is populated in WEKA by using Linear Regression to construct a measurement formula to be calculated with the captured data. Third phase is performance analysis and producing intelligent biofeedback

III. CAPTURING FINGER DATA FROM MOTION CAPTURE SENSOR

A. Comparing Internal Coordinate and TS-DH Coordinate Data

TS-DH is used in processing finger movement for analysis. The model produces an absolute coordinate output even on hand movement variation in rehabilitation. It helps to produce clean and significant graph movement for finger. Leap Motion Controller (LMC) is used to capture finger movement. LMC is infrared markerless affordable motion sensor that is capable of capturing forearm, wrist and hand movement [14].

The comparison uses two hands position and a data of finger joint coordinate, finger movement angle and bone length is captured into a database by using Unity 3D application with LMC.

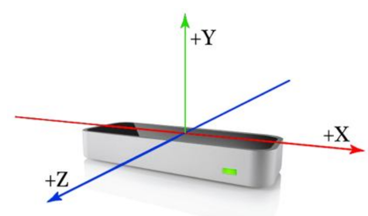

Fig.2: Leap Motion Coordinate Orientation

Figure 2 shows coordinate orientation for Leap Motion sensor which consists of X, Y, Z reading position and Z+ is points toward user. Hand user hovers above Leap Motion sensor which is mostly in -Z axis. Finger movement in Leap Motion sensor is captured on Y and Z axis.

Fig.3: Start Finger Position

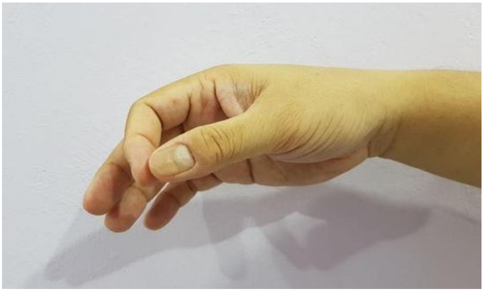

Fig.4: End Finger Position

Figure 3 shows normal hand position and Figure 4 shows the probability of hand position movement during virtual rehabilitation exercise. Index finger is used as an example.

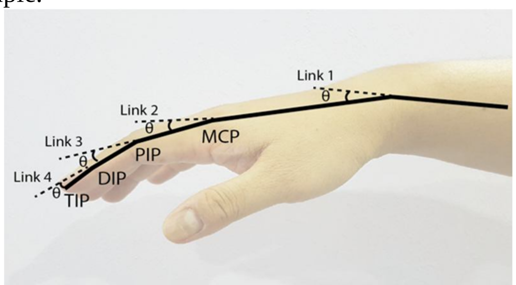

Fig.5: Assignation of Index finger detail

Figure 5 shows the assignation of index finger attribute for LMC joint data and TS-DH. For LMC coordinate joint, direct MCP, PIP, DIP and TIP data from LMC properties is captured, while for TS-DH angle for each link and length for finger bone is processed to produce MCP, PIP, DIP and TIP coordinate. All data is simultaneously captured.

Table 1: Internal coordinate value produced from motion capture

Figure	MCP	PIP	DIP	TIP
Figure 3	X=203.46	X=182.82	X=167.08	X=154.4
	Y=-27	Y=-59.28	Y=-74.13	Y=-82.75
Figure 4	X=188.94	X=184.82	X=171.64	X=161.38
	Y=-34.51	Y=-64.54	Y=-65.2	Y=-56.94

Table 2: Coordinate Calculated by TS-DH

Figure	MCP	PIP	DIP	TIP
Figure 3	X=65.56	X=94.46	X=106.06	X=111.80
	Y=10.58	Y=36.44	Y=54.92	Y=69.23
Figure 4	X=61.42	X=85.22	X=79.21	X=66.95
	Y=25.25	Y=55.87	Y=76.84	Y=86.19

Table 1 shows coordinate of Figure 3 and Figure 4 if direct coordinate position is produced from motion capture device and Table 2 shows coordinate of Figure 3 and Figure 4 with calculation of TS-DH model. The processed values for bone length in millimeter for Metacarpal is 66.41mm, Proximal is 38.78mm, Intermediate is 21.82mm and Distal is 15.42mm. The link values for Figure 3 are 8.34° for Link1**,** 32.73° for Link2, 15.87° for Link3 and 10.37° for Link 4. The link values for Figure 4 are 22.08° for Link1, 29.52° for Link2, 53.83° for Link3 and 36.44° for Link4.

Let's say Figure 3 is the starting position and Figure 4 is the ending position of rehabilitation for the same session.

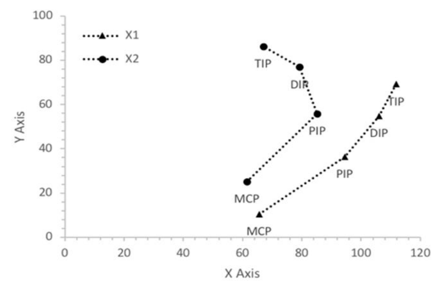

Fig.6: Coordinate of finger joint with TS-DH

Figure 6 shows generated graph of rehabilitation exercise session for finger movement calculated by TS-DH. X1 represents Figure 3 index finger position and X2 represents Figure 3 index finger position.

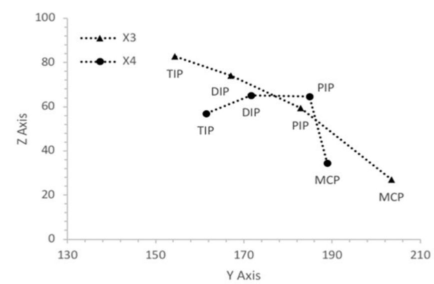

Fig.7: Coordinate of finger joint without TS-DH

Figure 7 shows generated graph of rehabilitation exercise session for finger movement direct from motion capture device. X3 represents Figure 3 index finger position and X4 represents Figure 4 index finger position. Z Axis data is converted into positive values.

Figure 6 graph is cleaner in terms of presenting a finger progress than Figure 7 graph for visual evaluation for therapist. It is more significant with major finger or wrist movement by time if visualized in the same graph. By using TS-DH, finger coordinate is in absolute position and always starts at 0,0.

B. Processing of Joint Angle

There are two parameters that is processed; joint angle and joint length then joint translation that is produced by TS-DH.

Data reference of finger progress measurement is produced and grouped in grasp, rest and extension state of fingers.

Fig.8: Finger Grasp Position

Fig.9: Finger Rest Position

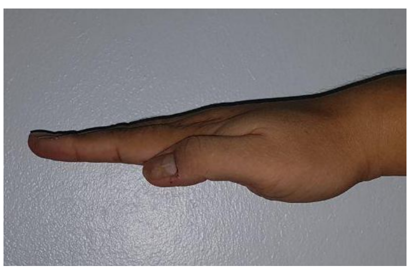

Fig.10: Finger Extension Position

Figure 8 shows grasp finger position, Figure 9 shows rest finger position and Figure 10 shows extension position when data is taken from LMC. Finger progress state is grouped by three measurements; 0 for grasp, 50 for rest and 100 for extension.

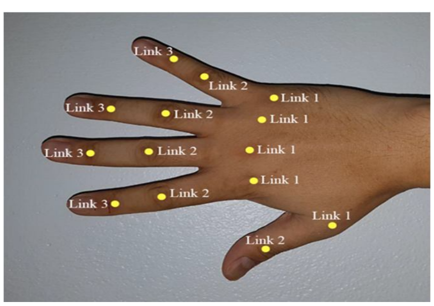

Fig.11: Link Details for fingers

Figure 11 shows the assigned link for each finger joint. Each of finger joint is given Link 1 to Link 3 from end of finger joint to direction of fingertip except for thumb which is only two links.

Table 3: Result of TS-DH coordinates for fingers

Finger	Link	Coordinate		
		Grasp (0)	Rest (50)	Extension (100)
Thumb	Link 1	X=24.82 Y=19.78	X=29.87 Y=10.72	X=28.2 Y=5.71
	Link 2	X=27.43 Y=41.42	X=48.19 Y=22.52	X=44.25 Y=17.21
Index	Link 1	X=20.67 Y=34.23	X=37.97 Y=12.54	X=34.76 Y=10.3
	Link 2	X=2.33 Y=47.27	X=52.06 Y=30.08	X=53.76 Y=17.68
	Link 3	X=-13.31 Y=44.4	X=56.19 Y=45.43	X=66.82 Y=23.81
Middle	Link 1	X=21.51 Y=39.38	X=41.58 Y=16.87	X=39.44 Y=9.92
	Link 2	X=-0.57 Y=53.99	X=56.65 Y=38.63	X=62.13 Y=17.72
	Link 3	X=-17.74 Y=50.66	X=60.03 Y=55.79	X=76.73 Y=23.91
Ring	Link 1	X=19.06 Y=36.96	X=38.4 Y=15.98	X=37.08 Y=6.83
	Link 2	X=-2.66 Y=50.86	X=52.74 Y=37.41	X=59.61 Y=13.01
	Link 3	X=-19.73 Y=47.53	X=55.79 Y=54.53	X=74.5 Y=18.23
Pinky	Link 1	X=15.08 Y=29.26	X=29.58 Y=14.44	X=28.78 Y=7.87
	Link 2	X=-0.25 Y=39.09	X=38.72 Y=30.2	X=44.25 Y=13.6
	Link 3	X=-16 Y=36.01	X=40.37 Y=46.16	X=57.49 Y=19.63

Table 3 shows the result of coordinate from TS-DH conversion by using value of links angle and bone length captured by LMC.

IV. PROPOSED MODEL OF FINGER STATE PROGRESS (FSP)

The data is populated in WEKA using Linear Regression to construct a measurement formula to be calculated with the captured data. Regression is commonly used in order to examine the correlation between variables [6].

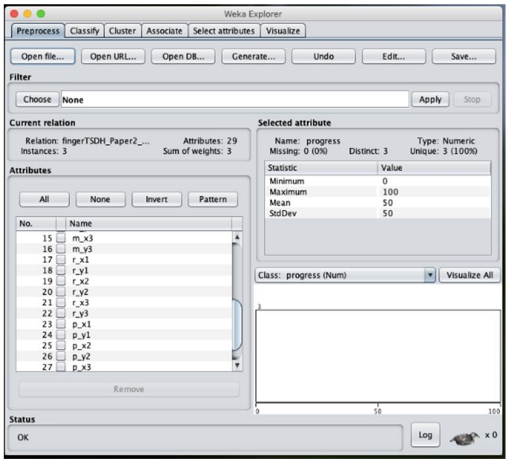

Fig.12: Data loading and selection for processing

Figure 12 shows Preprocess tab in WEKA application. CSV file that has been converted from Excel file which contains data that have been processed from motion capture device is loaded into WEKA. Variable or field from CSV file is using conversion as follows; (t for thumb, i for index, m for middle, r for ring, p for pinky)_((coordinate x or y)_(link number)). For example if the variable named i_x1, it is for x coordinate for Link 1 on index finger.

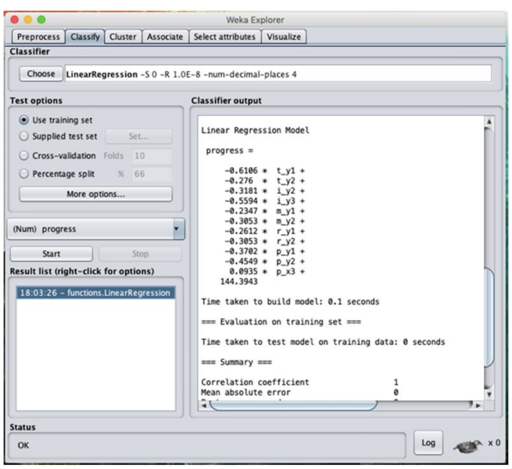

Fig.13: Result of Linear Regression processing

Figure 13 shows the output of Linear Regression method when data is processed into WEKA. Progress field is selected for processing output and training set option is selected.

Then the formula for Linear Regression Model:

progress = -0.6106 * t_y1 + -0.276 * t_y2 + -0.3181 * i_y2 + -0.5594 * i_y3 + -0.2347 * m_y1 + -0.3053 * m_y2 + -0.2612 * r_y1 + -0.3053 * r_y2 + -0.3702 * p_y1 + -0.4549 * p_y2 + 0.0935 * p_x3 + 144.3943 (1).

V. RESULT & DISCUSSIONS

Let's say we have an example data of finger movement for a stroke patient.

Table 4: Example of TS-DH coordinates for fingers

Finger	Link	Coordinate
Thumb	Link 1	X=29.03 Y=7.17
	Link 2	X= 43.9 Y=21.32
Index	Link 1	X=34.51 Y=15.13
	Link 2	X=49.95 Y=29.65
	Link 3	X=58.16 Y=42.19
Middle	Link 1	X=37.65 Y=19.21
	Link 2	X=53.6 Y=38.38
	Link 3	X=60.31 Y=53.43
Ring	Link 1	X=35.37 Y=16.86
	Link 2	X=51.59 Y=34.94
	Link 3	X=58.89 Y=49.61
Pinky	Link 1	X=28.78 Y=11.56
	Link 2	X=41.23 Y=23.35
	Link 3	X=49.12 Y=36.25

Table 4 shows an example movement of five fingers produced by TS-DH formula.

So the calculations for progress by using Linear Regression formula are:

-0.6106 * 7.17 + -0.276 * 21.32 + -0.3181 * 29.65 + -0.5594 * 42.19 + -0.2347 * 19.21 + -0.3053 * 38.38 + -0.2612 * 16.86 + -0.3053 * 34.94 + -0.3702 * 11.56 + -0.4549 * 23.35 + 0.0935 * 49.12 + 144.3943 = 59.493505

Since we normalized progress by range of 0 to 100, we can conclude that an example data has 59.49% finger progress movement between the range of grasp (0) and extension (100). The progress percentage can be analyzed for different points of view either for grasp progress or extension progress.

VI. CONCLUSION

In conclusion, FSP model is very useful as a measurement model for any virtual environment in developing fine motor exercise application for therapists. The model can be implemented for real-time value to be projected as Graphical User Interface (GUI) or can be analysed between multiple rehabilitation sessions. In the future, FSP model may be used not only for fine motor but also to measure gross motor progress by using a combination of several motion or more advanced motion capture sensor.

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