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The Gross Motor Function Estimation of Upper Extremity with Simple Daily Living Activities for the Outcome Measurement: Design, Development, and Automation

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Abstract: The main objective of the work is to develop an instrumented hand function test system to assess the gross motor function of the upper limb in human beings. Simple day-to-day activities are selected for the test item generation, and they are: i) displacement of cylindrical object and ii) pouring water into a cup test. The trajectory of hand movement and position values obtained from the Logitech B525 USB camera are fused with the motion data from MPU6050 and further linearized through the Extended Kalman Filter. The activity time is automatically calculated using the developed instrument. Also, the acceleration, orientation, trajectory plots of the object movement, and mean force are captured using the sensor fusion technique. Spearman's rank correlation coefficient is above 0.9, representing a high correlation between the traditional stopwatch and automated test methods. Manual stopwatch usage is avoided, which reduces the clinician's burden. The method is more useful as patients need not visit the physiotherapy center each time for outcome measurement.

Keywords: *Daily activities, Hand function test, Instrumented test battery, Inertial sensor, Sensor fusion*

1. Introduction

Our hand plays a significant role in various activities of our day-to-day life. The function of the upper limb may change depending on aging, injury, or health issues related to the nervous system. Proper rehabilitation is required to regain functional movement. Through a variety of assessments, the rehabilitation's effectiveness is evaluated. Hand evaluation instruments fall under the categories of performance-based measurements or self-report measurements. The ordinal scales used to assess self-report measures have the drawback that the evaluation would be subjective, not standing the clinician's expertise [1]. In the performance-based step, the activities similar to our daily living are measured using a stopwatch manually. In this measure, the final score depends on the time taken to complete the test and is considered more objective [2]. In the traditional performance-based test, the clinician must concentrate on the stopwatch during test execution. Delay may exist while operating a stopwatch, known as 'response time.' Also, time calculation alone cannot give complete details of the upper limb performance. Along with time calculation, parameters such as motion trajectory of the limb, amount of force applied while gripping, and peak point of the trajectory give subtle and detailed information about upper limb performance, which is otherwise not visible from clinical scales.

The automation in upper limb assessment is also helpful in reducing the laborious process of expensive interventions [3–5]. For all these reasons, developing an automated version of quantitative upper limb assessment is gaining high priority these days.

The available test items in literature, either use sensors on the body or based on the image or video recording of the assessment [6–8]. Whenever a patient's hand is tied with some sensors or video capturing is done, they will be more conscious, and the assessment outcome may not be realistic. This research aims to develop an automated hand function test battery called an "Instrumented hand function test battery," having sensors on the test items and the hand is free for the movements. The automation reduces clinician supervision time and assesses the upper limb with minimum infrastructure. This paper is divided into five sections: Section one briefly introduces the work. The second part gives details on related work. The third part is materials and methods, focusing on the test materials, upper limb assessment standardization, and sensor fusion implementation. Section four briefs about the results obtained and statistical analysis. Moreover, section five discusses the results, and section 6, conclusions of the work, respectively.

2. Related Works

The literature on automated hand function tests for upper

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limb rehabilitation is extensive and offers valuable insights into the development and effectiveness of such assessment tools. Some commonly used automated hand function tests include the Box and Block Test, Nine-Hole Peg Test, Jebsen-Taylor Hand Function Test, and Sollerman Hand Function Test [9–11]. Wearable and vision sensors are two broad categories available for upper limb assessment.

2.1. Wearable device-based upper limb assessment

One notable area of research in automated hand function tests is the development of wearable device-based assessment methods. These methods involve wearable sensors, such as accelerometers and gyroscopes, to capture and analyze the movement patterns and kinematics of the upper limb during functional tasks. These wearable devices provide real-time data on hand function and can be used in clinical and home-based settings, allowing for continuous monitoring and assessment of rehabilitation progress. Furthermore, wearable device-based assessment methods have the potential to overcome some of the limitations associated with traditional hand function tests [12-13].

An assessment of the state of upper-limb wearable device research and its practical application by Mingjie Dong et al. identifies existing design approaches, evaluates their merits and shortcomings, and identifies emerging research directions [14]. This study offers a systematic and thorough overview of upper-limb wearable device research, encompassing wearable design, sensor technologies, wearable computer methods, and wearable applications. The review provides a thorough overview of the area and can direct future studies in creating more effective wearable sensors for the upper limbs. Xiupeng Gao and Yiwei Yin designed a wearable armband device to assess the upper limbs' motion function. The device uses inertial sensors to analyze and calculate the tester's upper limbs' acceleration and angular velocity signals to evaluate the motor function [15]. The report notes that there are still specific design issues, such as the equipment's stability in the presence of electromagnetic interference from a complex environment and the integrated display of equipment networking, which will be the focus of future research.

Luis Paredes et al. present FabHandWear, an end-to-end pipeline for designing and fabricating customized functional hand wearables [16]. The system allows users to create wearables that fit their hands perfectly and provide the specific functions they need. The system's current support for hand wearables design is based on a parametrized five-finger hand structure, which may not be inclusive to all users. Alessandra Angelucci et al. proposed a brand-new graphic test called SpAcCo for measuring the dexterity of the dominant hand as a measure of fine motor disability [17]. One advantage is that it enables quantitatively parametrizing temporal and spatial performances, allowing for a more precise and objective assessment of fine motor disability. However, the downside of this test is that individuals with severe impairment may not be able to complete the test within the given time limit, which could affect the accuracy of the assessment.

Naoya Yamamoto et al. aimed to investigate using ring-shaped wearable devices to quantitatively measure finger usage in stroke hemiplegia patients and compare the results with traditional clinical evaluation outcomes [18]. The instrument measures the angular variation of the PIP joint or proximal interphalangeal joint. It describes the cumulative change as the quantity of finger usage, enabling practical measurements. Future studies with higher sample sizes could produce more reliable results because the study only used a small number of participants.

2.2. Vision and inertial filter fusion-based upper limb assessment

Orestis N. Zestas et al. developed a computer-vision-based hand rehabilitation assessment suite that can be used remotely by patients and therapists to normalize the scores of the Sollerman hand function test and the Purdue Pegboard Test (CV-BBT) for different age groups [19]. The suite incorporates various well-known and often used hand rehabilitation and evaluation assessment tools packaged as a standalone desktop application using modern computer vision functionalities. It is important to remember that creating any virtual exercise or evaluation test for hand rehabilitation can be extremely challenging and time-consuming, and its validity must be carefully considered.

Table 1. General characteristics of the participants

Experiment with time scores in seconds	Age Group (years)			
	20-35	36-50	51-65	66-80
Cylindrical object displacement	3.02 ± 0.61	3.43 ± 0.52	4.18 ± 0.66	5.35 ± 0.66
Pouring water from one cup to other	5.64 ± 0.25	5.89 ± 0.26	6.24 ± 0.26	7.70 ± 0.64

Data expressed in mean ± SD; SD-Standard Deviation

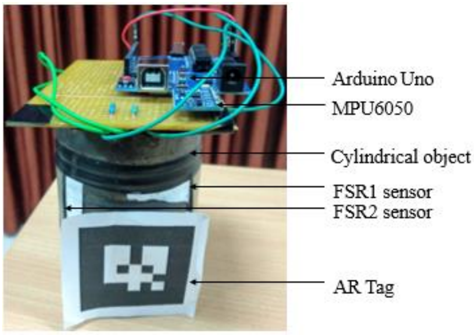
Manlio Massiris Fernández et al. developed a novel method for ergonomic risk assessment using computer vision and machine learning [20]. The technique detects the skeletons of the employees, infers the positions and angles of their body joints, and then computes the Rapid Upper Limb Assessment (RULA) scores. The method was tested with limited videos, and the results may not be generalizable to all working scenarios. Also, this method requires a certain level of technical expertise to implement, which may limit its accessibility to some users.

2.3. Findings from the existing motion capture methods

Yahya et al. reviewed motion capture techniques for upper extremity assessment [21]. This includes four different motion capture technologies: Optoelectronic measurement systems, Image processing systems, Mechanical measurement systems, and Inertial measurement systems. The wearer is probably inconvenienced by the location of the marks on the body. Furthermore, getting accurate measurements of human physical activity outside the lab under free-living circumstances has been challenging [22-23]. The mechanical systems, including strain gauges, capacitive pressure sensor arrays, or motion suites with flex sensors, can be wearable sensors woven into clothing or hand gloves. In home-based upper limb assessment, the sensor positioning inaccuracy and calibrating the sensors each time before usage is problematic [24-25]. A general observation is that whenever some wearable devices are placed on the body, the person performing the task becomes more conscious, resulting in data that may not reflect the actual performance. This affects outcome measurement, and recorded measures may not reflect the scenario in the patient's home setting.

3. Materials and Methods

The 'instrumented object' is designed and developed for the upper limb assessment, as shown in Fig. 1. It has an Arduino Atmega328P microcontroller, MPU6050 IMU sensor, Force Sensitive Resistor (FSR) sensors, and a Logitech B525 USB camera. This facilitates free hand movement, freeing the body from wearable devices [21], [26]. FSR sensors are used to evaluate hand function, which measures force distribution in fingertips and thumb during the task's object grasp and transport phase. The algorithm is run on Ubuntu 18.04, a Linux-based open-source operating system using the Robot Operating System (ROS) framework. ROS uses the 'cameracalibrator.py' node from camera calibration to calibrate a monocular camera with the help of a 9×7-inch checkerboard. The test items are 1) displacement of cylindrical object and 2) pouring water into a cup. The cylindrical object with height = 11cm, diameter = 7.5cm, and weight of the object = 450g is used for the experiment. The general demographical characteristics of the participants are listed in Table 1.



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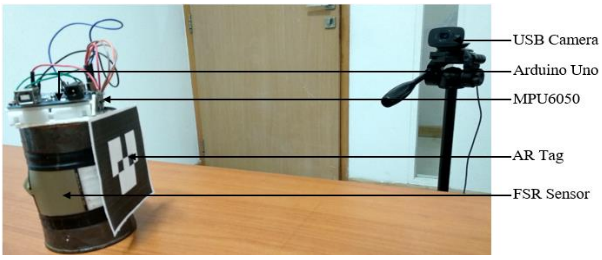


(b)

Fig. 1. Instrumented object (a) Embedded with sensors (b) Setup table with instrumented test battery and USB camera.

The schematic of Fig. 2 is used for pose (position and orientation) estimation in the displacement of a cylindrical object and pouring water task. An 8-bit AVR-based ATMEGA328P-AU microcontroller with 32 pins is employed in this work. The circuit consists of two FSR sensors, one MPU6050 IMU sensor, and a computing system for pressure and orientation measurement.

3.1. Implementation of vision and inertial fusion using Extended Kalman Filter

The Extended Kalman Filter (EKF) package estimates the object's pose in upper limb assessment. The instrumented object consists of an Augmented Reality (AR) tag and an IMU sensor, as shown in Figure 1 (a). The USB camera tracks the AR tag and estimates the 3D pose in six degrees of freedom. The motion data received through MPU6050 and position values obtained from the USB camera are fused and linearized using the EKF package. While relative angular velocity could be used to calculate the object's heading, EKF uses linear acceleration to estimate the relative position of a moving item. The complete workflow of movement tracking is shown in Fig. 3. The two activities, displacement of a cylindrical object and pouring water into a cup in sequence, are given to each participant individually. The dominant hand was used to complete the tests first, then the non-dominant hand.

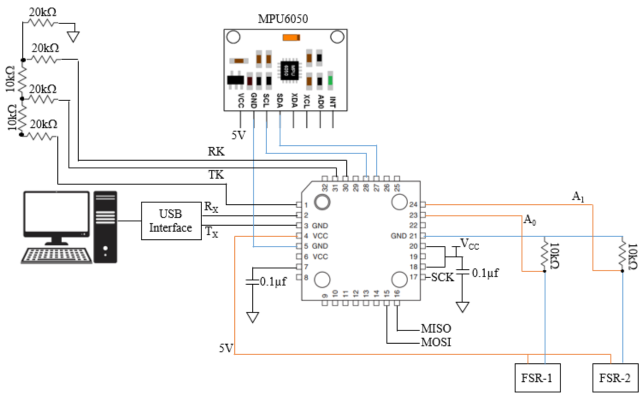


Fig. 2. Schematics of circuit diagram used for pose estimation in gross motor function

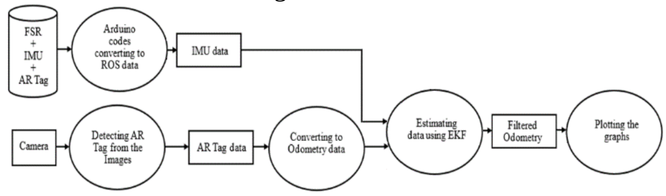


Fig. 3. Workflow diagram of movement tracking test

3.2. Displacement of Cylindrical Object

The gross motor of the hand during object movement is assessed by observing the trajectory of motion and grip strength by a pressure sensor. FSR assembly is a 4.45cm × 4.45cm thick polymer film that detects force ranging from 0.1N to 10N. MPU6050 gives the orientation information, and the USB camera gives the motion trajectory. In this task, the grip force is analyzed by asking the participant to lift the instrumented cylindrical object, hold it for some time, and place it on the table. The procedure is standardized, i.e., seating arrangements, test items position, and test instructions are defined before the test. The activity is repeated with the non-dominant hand. The trajectory of hand motion, orientation, and force applied during object manipulation are plotted, and the total time to complete the task is recorded. The cylindrical object displacement involves the shoulder complex's range of motion and flexibility. Quantitative parameters such as orientation, hand trajectory, and pressure applied on cylindrical objects are recorded. A flowchart of the automated version of the displacement of cylindrical object task is depicted in Fig. 4.

The program starts once the camera detects the AR-tag-attached object. When holding a cylindrical object, FSR triggers the timer and records applied pressure. This recording continues until the completion of placing the cylinder 15cm above the table. The timer stops once the hand leaves the object. Force values will be plotted and displayed with fused sensor data, i.e., orientation and position information.

3.3. Pouring water into a cup

Internal rotation is often associated with forearm pronation, and its functional analysis is examined with the help of pouring water into a cup. The start, grasp, and pouring positions are depicted in Fig. 5. The hand is returned to the original position (position 1). The role of the thumb and ring finger is more significant in pouring water into a cup. Force distribution during the grasping phase is important in analyzing hand function. A cylindrical shape of 7.5cm diameter and 11cm height is selected considering the hand size of an average adult. Force sensing is recorded and plotted with the total task time. In this task, importance is given to the analysis of internal rotation often associated with forearm pronation.

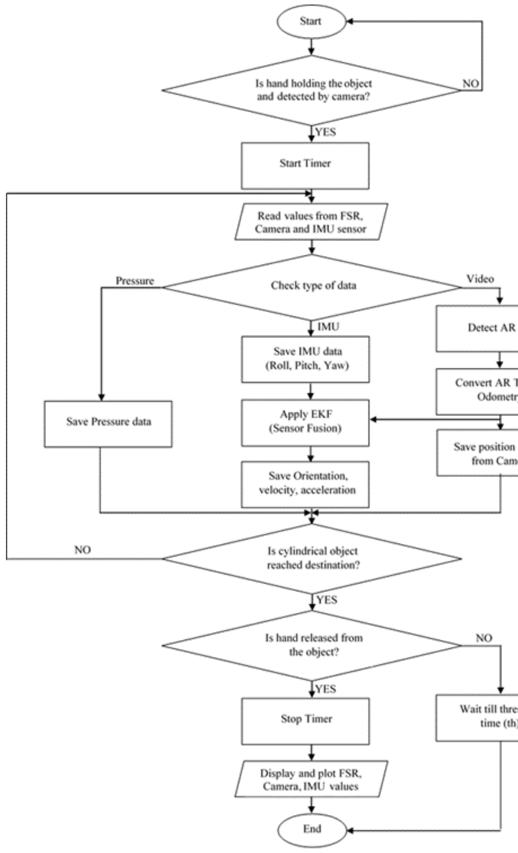


Fig. 4. Automation flow diagram of displacement of cylindrical object task

Fig. 5. Participant performing pouring water into a cup task

A flowchart of the automated version of the pouring water into a cup task is shown in Fig. 6. The 100ml water is filled and sealed in a cylindrical object, and the pouring action is performed into the other cup. This arrangement gives a required grip force to lift the water-filled cylindrical object and avoids water spillage during the test process. Two FSR sensors on both sides of the cup record the thumb and other digits' grip force, and MPU6050 measures orientation during the task. The participant holds the cylindrical object after the start command from a clinician. Timing records start once the participant holds the object and stop when he returns his hand to the table. Simultaneously trajectory will also be plotted along with the pressure variation plot. A USB camera, which is kept 1.6m away from the participant, is sufficient to record all these movements. If any occlusion is present for a short duration, MPU6050 sensor gives the relative displacement, and fused data (Camera+MPU6050) gives good trajectory information.

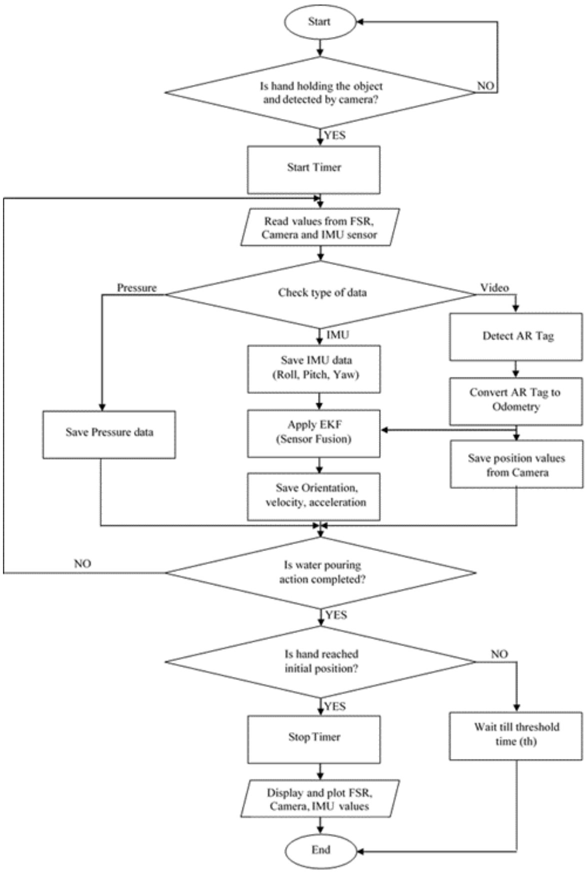


Fig. 6. The automation flow diagram of displacement of pouring water into a cup task

4. Results and Analysis

The demographic details of the participant, such as age, sex, and dominant/non-dominant hand details, are considered during the test procedure. Further, the two activities used in the study are displacement of cylindrical objects and pouring the water experiments' skewness, and median values are visualized using a Box plot.

4.1. Gross motor function test using Cylindrical Object

Fig. 7 shows the correlation between traditional and automated tests. The following correlation classification was used: no or very low: p = 0 - 0.25; low: p = 0.26 - 0.40; moderate: p = 0.41 - 0.69; high: p = 0.70 - 0.89; very high: p = 0.90 - 1.0. A non-parametric test, i.e., Spearman's rank correlation, is used to check the relation between traditional stopwatch and automated method, as the test results are time, which is a continuous variable. It is observed that traditional and automated methods are highly correlated with rs = 0.992.

The four age groups were observed for the outcome measurement in terms of time taken to complete the test using the dominant hand. The probable error estimation among different age groups is shown in Fig.8. It is observed that the automated test gives similar results as the traditional test. However, the advantage of the automated method is that the clinician is free from noting down the time through the stopwatch, and there could be human errors, i.e., action perceived and action taken or noted down. Auto recording of quantitative parameters and maintaining a database of complete test sessions help the clinician for further follow-ups.

4.1.1. Color/Grayscale figures

Figures that are meant to appear in color, or shades of black/gray. Such figures may include photographs, illustrations, multicolor graphs, and flowcharts.

4.1.2. Line Art figures

Figures that are composed of only black lines and shapes. These figures should have no shades or half-tones of gray, only black and white.

4.1.3. Tables

Data charts which are typically black and white, but sometimes include color.

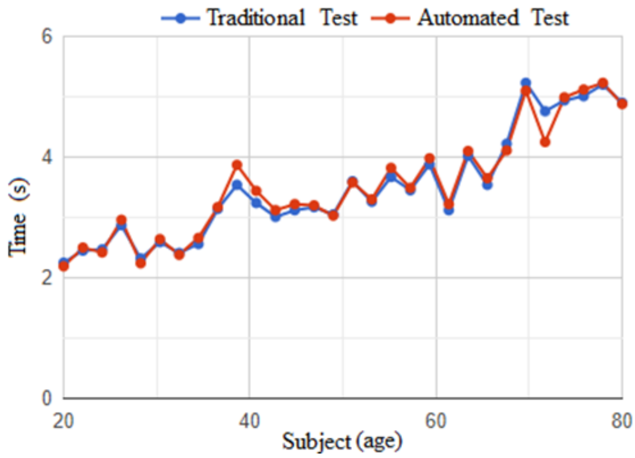


Fig. 7. Correlation plot of the cylindrical object test

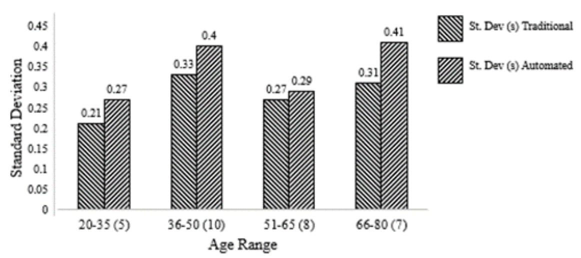
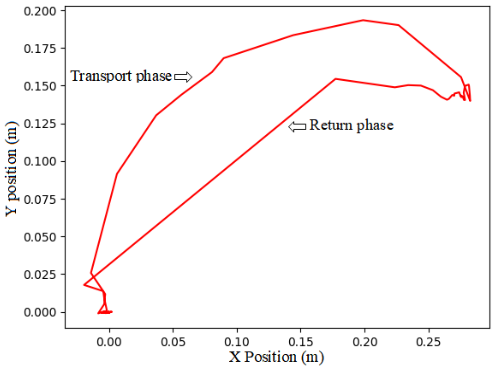


Fig. 8. The probable error estimation of the traditional and automated version of the cylindrical object displacement test

4.2 Gross motor function test using Pouring water into a Cup

To examine grip force and force sharing during grasping, pouring water into a cup is considered. The vision output from the camera is plotted in Fig. 9 (a), which shows the trajectory of lifting the cup, bending to pour the water, and then resuming the initial posture. The plot shows two tracks that represent the transport and return phases. The transport phase corresponds to the initiation of lifting the cup and pouring action. The return phase is keeping the cup back in its original position. Fig. 9(b) is the Kalman filter output plot obtained by combining the vision and IMU data. Orientation output in radian is seen in Fig. 9(c), which shows that the roll angle (X-axis) variation is predominant compared to the other two axes (Y and Z) while pouring water into a cup. Fig. 9(d) is the FSR output in the Newton unit.



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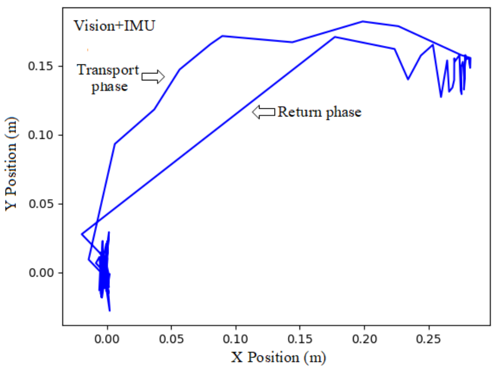

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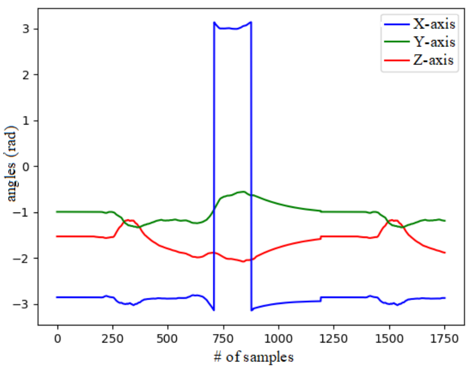

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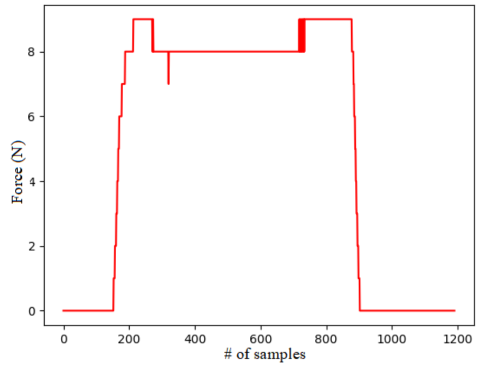


(d)

Fig. 9. Output trajectories of the pouring water task (a) Only camera output (b) Filtered output from vision and IMU sensor (c) Orientation of the IMU sensor (d)FSR pressure sensor output

After completing one test, the computer's terminal window displays quantitative values related to maximum and mean grip force in Newton (N), hand movement trajectory in meters, and total time taken to perform the task. The screenshot is shown in Fig. 10. Further analysis can be made using the recorded video.

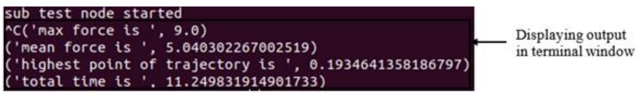


Fig. 10. The screenshot of a terminal window: maximum and minimum force(N), the highest point of trajectory(m), and test completion time(s)

In the case of pouring water from one cup to another, rs = 0.983, i.e., positively correlated between traditional and automated methods. The same participants are used in this test item, and the output is plotted as shown in Fig. 11. The test session is performed as per the standard procedure, and readings are recorded automatically. The automated test item version works as well as the traditional test method. Participants could not find any difference between these two test processes.

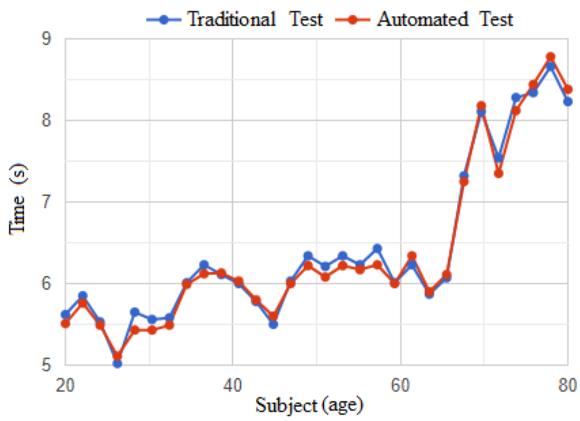


Fig. 11. The correlation plot of pouring water into a cup test

Fig. 12 indicates the probable error estimation for pouring water into a cup test using a traditional stopwatch-based and developed automated test setup. The overall trend is that hand function significantly declined with increasing age. During this task, the age range in the 66-80 years' category took longer than the 20-35, 36-50, and 51-65 age groups. Female individuals are faster compared to male individuals. The possible reason for this result could be that participants in the 51-65 age group in the female category were homemakers, and their occupation experience mainly influenced the execution speed.

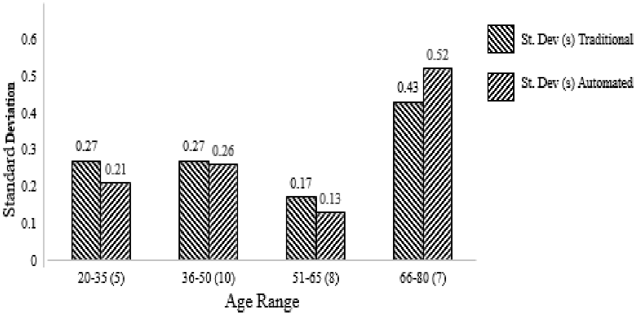


Fig. 12. The probable error estimation of the traditional and automated versions of pouring water into a cup test

Participants are selected randomly between the age group of 20 to 80 (sample size=30). SPSS for Windows, version 20, calculates all the statistical analyses with a p-value set at 0.05. The independent sample t-test is performed to estimate if there is any significant difference in the demographical characteristics of the participants in the two selected experiments. Also, to see any effect of different age groups on the said experiment, Analysis of variance (ANOVA) is performed. The data's normality is checked using the Shapiro-Wilke and Levene's tests to test the variances' equality.

5. Discussion

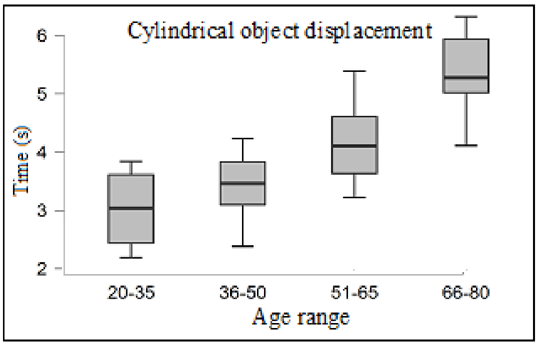
The proposed work is conducted and tested with healthy participants to check the feasibility of automation in upper limb assessment using standardized test items. Testing on the patient population is the future scope of the work. The participants' demographic details, such as age, sex, and dominant/non-dominant hand details, were considered during the test. Table 2 shows the result of the t-test analysis, indicating the Cylindrical object displacement has a significant mean difference between the dominant hand and non-dominant hand (p-Values< 0.05) and t-statistics (> 2.00) for 58 degrees of freedom.

Table 2. Between groups, comparison of handedness (hand dominance) on test scores

	Handedness	Mean	SD	-value	ignificance (p<0.05)
Cylindrical object displacement	Dominance	3.5287	).8962	-3.971	<.001* (S)
	Non-dominance	4.4867	).9707		
Pouring water from one cup to other	Dominance	6.3887	..0200	0.250	).804 (NS)
	Non-dominance	6.3330	).6700		

*indicates highly significant; S-Significance; NS- No Significance; SD-Standard Deviation

The non-dominant hand requires more time to complete the cylindrical object displacement task than the dominant hand. Pouring water from one cup to another experiment resulted in no significant difference between the time taken by the dominance and non-dominance hand (p-value >0.05). The test data are recorded in time (seconds), a continuous variable; hence, a non-parametric test is applied to check the correlation between traditional and automated methods, i.e., Spearman's Rank Correlation. The box plot in Figure 13 shows that the median time taken to perform the task increases over the different age groups. One can also observe that as age increases, more time is taken to complete tasks. The test results show that traditional stopwatch-based and automated time calculations are highly and positively correlated for cylindrical object displacement (rs = 0.992) and pouring water task (rs = 0.983). The added advantage of the automated method is less clinician interference uniformity in scoring, and a database of the test scores of every session can be maintained for future analysis. Hence, it increases the reliability of outcomes and certainly helps clinicians spend more time on further guidance on therapeutic aspects. The proposed work assesses the hand's natural movement without any wearable device. The developed setup can also be used at home for hand assessment.



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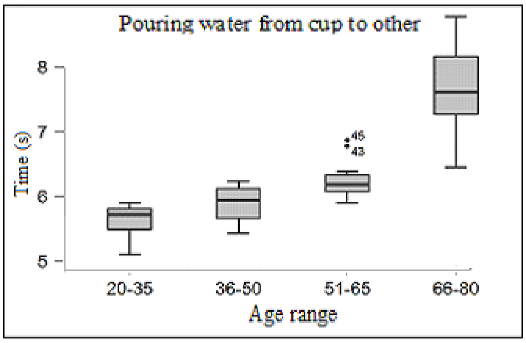

(b)

Fig. 13. The box plot shown for the four age groups for the gross motor function test using (a) cylindrical object displacement, (b) Pouring water into a cup

6. Conclusion

Existing tests require a clinician to administer and monitor the timing information of the assessment using a manual stopwatch. In a hospital setup, assessing requires significant time and patience from the clinician. This automated version presented in this research work increases the reliability of outcomes and certainly helps clinicians in guiding further action on therapeutic aspects. In addition, the algorithm also checks if the specific sequence is followed or not in performing the task. While performing the test, following a specific sequence always brings uniformity, which helps assess the improvement during the subsequent visits. Ongoing research and technological advancements hold promise for developing more effective and accessible assessment tools in hand function tests for upper limb rehabilitation. These tools can potentially revolutionize upper limb rehabilitation by providing objective measurements, personalized interventions, and improved outcomes for stroke patients.

Author contributions

Sucheta V. Kolekar: Conceptualization, Methodology, Software, Field study.

Aneesha Acharya K.: Data curation, Writing-Original draft preparation, Software, Validation. Field study

Somashekara Bhat: Visualization, Investigation

Kanthi M.: Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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