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DEVELOPMENT OF AN INSTRUMENTED OBJECT TO BE USED IN A NEW UPPER LIMB PROSTHESIS TRAINING PROTOCOL

Pedro de Figueiredo Abissamra

IFSP – São Paulo Federal Institute of Education, Science and Technology.
Rua Pedro Vicente, 625 – Canindé – São Paulo – SP – Brasil – CEP: 01109-010
pedro.abissamra@aluno.ifsp.edu.br

Jean Mendes Nascimento

USP - University of São Paulo
Avenida Professor Mello Moraes, 2231 – Cidade Universitária – São Paulo – SP – Brasil – CEP: 05508-970
jeanmendes@usp.com.br

Ana Carolina Rodrigues da Silva

AACD – Disabled Childrens Assistance Association
Avenida Professor Ascendino Reis, 724 – Ibirapuera – São Paulo – SP – Brasil – CEP: 04027-000
ancsilva@aacd.org.br

Paulo Marcos de Aguiar

IFSP – São Paulo Federal Institute of Education, Science and Technology.
Rua Pedro Vicente, 625 – Canindé – São Paulo – SP – Brasil – CEP: 01109-010
pmaguiar@ifsp.edu.br

Abstract. *The impairment of grasping ability is very frequent in new prosthesis users. More than half of them remain with significant difficulties to control the prosthesis during prehension tasks, which often leads to discontinuation of use. Usually, the patients are trained with the prosthesis by grasping and releasing some objects. Both the patient and the therapist do not have any other feedback information except the vision, as it is done in one of the most popular clinically validated score-based hand function tests, the Southampton Hand Assessment Procedure. However, to get more reliable therapy results, it is essential to have more information about the patient's training, such as gripping force and the prosthetic hand orientation. The Intelligent Object prototype developed comes to bridge the gap between functional scores training and measurable function training, leading to reliable therapy results. The Object was printed in Acrylonitrile Butadiene Styrene using a Fused Deposition Modelling printer, inner it there are a 5-kilogram load cell and a 6 degrees of freedom Inertial Measurement Unit. The object shape was defined based on the prostheses in use and the human hand. This paper presents the Intelligent Object development, its tests and the preliminary results that looks promising.*

Keywords: *Instrumented Object, Upper Limb Prostheses, Development, Training Protocol.*

1. INTRODUCTION

Hand prostheses or upper limb prostheses should provide functional replacements and visual comfort of lost hands. The purpose is to allow amputees to regain autonomy and abilities in their daily life (Weiner et al., 2022). Despite the hand being one of the most complex parts of the human body in terms of mechanical construction, performance and execution, many efforts have been dedicated to restoring all these functions in the best possible way for amputees.

Myoelectric controlled prosthesis hand has been developed since the late 1960s and became more commonly available in the 1980s (Widehammar et al., 2021). Over the last 20 years, researchers have been working to solve the problems related to upper limb prostheses, such as the difficulty of control and the rejection rate (Nascimento et al., 2021). Currently, these prostheses contain the highest level of technology embedded, using great processing, good controls techniques, precise instrumentation and Machine Learning algorithms (Kristoffersen et al., 2021). This kind of upper limb prosthesis is widely used and, in various different degrees, from daily use of the functions to only wearing the prosthesis occasionally or wearing it frequently but not using its functions at all. Hence, several studies suggest that prostheses are frequently abandonment and some reasons that may justify this fact are: limitations in terms of intuitiveness-of use; a high level of user control effort to execute grasping tasks; dissatisfaction with the functionalities and insufficient training process is also a commonly reported problem (Smail et al., 2021; Weiner et al., 2022; Widehammar et al., 2021).

The aspect of training strategy has been an important discussion among rehabilitation specialists. It is known that quality of training determines the use of the prosthesis for the rest of one's life. Therefore, training methods have to be developed in a way that functionality in everyday life will improve, consequently the training activities needs to be performed in an everyday context (Bouwsema et al., 2008; Law et al., 1996). Usually, the patients are trained with the

prosthesis by grasping and releasing some objects. However, the patient and the therapist do not have any feedback information during the training except the vision, this lack of information can impair the efficiency of the training and consequently use of the prosthetic device.

The idea of this study is to develop an instrumented object that allows the elaboration of a new training protocol based on reliable information collected during training activities. The so called Intelligent Object (IO) is modeled to fit properly in a myoelectric prosthesis model already developed by (Nascimento et al., 2021) or in any human or prosthetic hand, and has built-in instrumentation to capture the prosthesis orientation, and the applied force on the object. A friendly interface is also developed that allows the therapist to visualize and analyze the training execution in not only in real time but also the historical measures from the last 30 minutes.

It is expected that the IO can be used combined with some functional scores and measurable function training protocols, such as the Southampton Hand Assessment Procedure (SHAP). The SHAP is one of the most popular clinically validated hand function tests and consists in 26 self-timed tasks (12 abstract tasks and 14 activities of daily life). The subjects' time measure is recorded for each task, then a score, called Index of Functionality, is calculated as a metric of the one's function (Light et al., 2002). However, functional scores are not enough. In order to get a more reliable therapy results, it is essential to have more information about the patient's training, such as gripping force and the prosthetic hand orientation. Therefore, by combining the information acquired from the IO with functional scores, a new training protocol can be developed aiming to improve the therapy results and consequently aiding the patients to have a better life.

2. METHODOLOGY AND RESULTS

In this section, the device development is shown step-by-step divided in 5 main steps, and some steps are followed by its tests and results. In the first step (2.1) the object's case was designed and printed using Fused Deposition Modelling (FDM) technology. In the second step (2.2) the load cell was implemented, its code was developed, and the mechatronic system was tested. In the third step (2.3) the Inertial Measurement Unit (IMU) was implemented and tested. In the fourth step (2.4) another code was done to merge the load cell and the IMU codes and send the readings to a Node-Red dashboard, turning the IO into an Internet of Things Device. Finally, in the fifth step (2.5), with the IO device complete, an orientation test was carried out.

2.1 Object's Case

The Intelligent Object's case was developed with the Inventor Computer Aided Design (CAD) software. A model was created and printed in Acrylonitrile Butadiene Styrene (ABS) using a FDM printer.

The object is a 30mm diameter cylinder to be used to evaluate the medium wrap power grip, since this gripping pattern is considered the most daily used pattern (Feix, et al., 2016). Figure 1(a) shows the printed object case mounted, while the other two figures (b and c) show the inner and the exterior part of the unmounted object, respectively. In the inner part there is a support for the placement of the load cell.

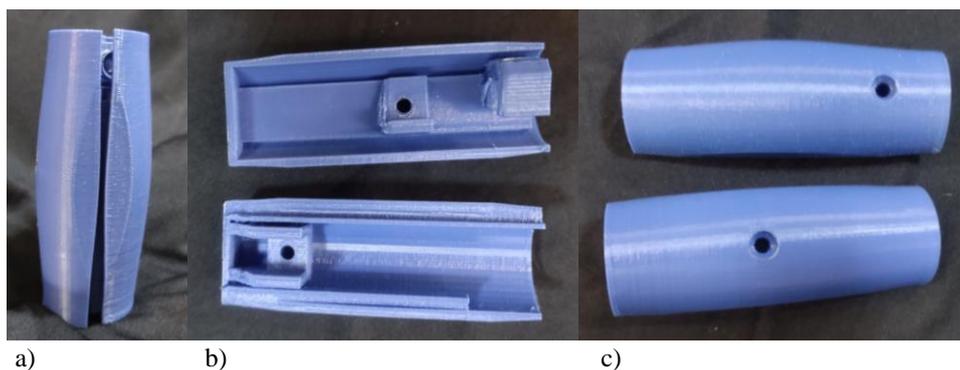


Figure 1. Intelligent Object Case

2.2 Load Cell Application

A 5 Kg RoHS single point load cell was used to get the power grip strength measures. The load cell was connected to a HX711 amplifier module, that sends the data to the ESP32 microcontroller (μ C). The electrical diagram can be seen in Figure 2.

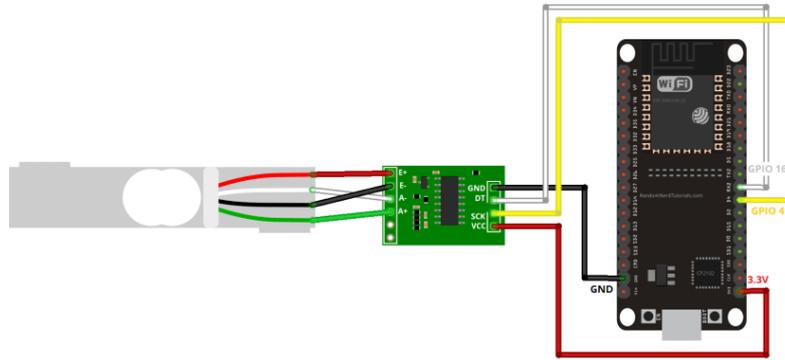


Figure 2. Load Cell and HX711 Electrical Diagram

The μC was programmed through the Arduino IDE, and the HX711 library was used. A measure adjustment was needed to be performed on the code, once that the readings provided by the amplifier module did not match the real weight that was being measured. To accomplish this, a known weight was placed on the load cell as shown in “Figure 3” and the adjustment was done successively until the measurements reached the correct value.



Figure 3. Measure Adjustment Procedure

Once the adjustment was concluded, a validation was executed using four objects with different known weights seen in “Figure 4”. Each of them was placed on the load cell and an average of the last 100 measures was taken and compared to the expected value, which was measured using a precision balance, to calculate the error.

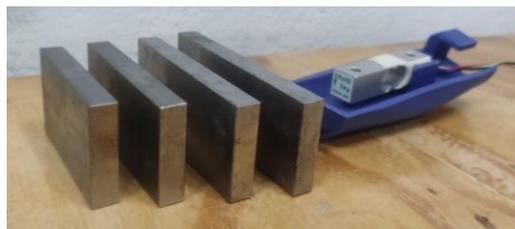


Figure 4. Objects used to validate the load cell adjustment.

The adjustment validation tests results from each of the four objects are shown in Table 1. The maximum error obtained was 1.32g, that corresponded to a 0.91 percentual error.

Table 1. Error obtained during load cell adjustment validation.

Expected (g)	Measured (g)	Error (g)	Error (%)
144.32	143.00	1.32	0.91%
169.83	169.00	0.83	0.49%
194.23	193.00	1.23	0.63%
217.85	217.00	0.85	0.39%

2.3 Inertial Measurement Unit

The IMU used in this work was the MPU6050, a six degree of freedom sensor, that was attached directly to the ESP32 and communicates with it using I2C protocol. The electrical diagram can be seen in “Figure 5”.

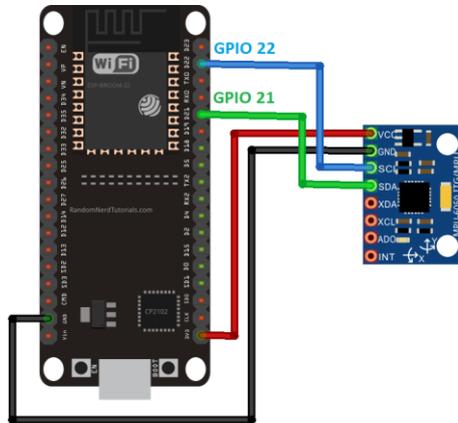


Figure 5. MPU6050 Electrical Diagram

As it was done with the load cell, the IMU readings were also taken with the ESP32, that was programmed using the Arduino IDE. To get the measurements, the “wire” Arduino library was used to communicate via I2C protocol. The data returned is the acceleration values in each one of the three axes, X, Y and Z, and an offset was added to make sure that the readings are correct. To calculate the orientation of the sensor, and, consequently, the orientation of the object, the acceleration module is calculated then the angle with each one of the three axes is calculated using the scalar product formula. The IMU frame can be analyzed in “Figure 6”.

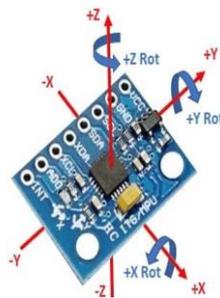


Figure 6. Inertial Measurement Unit Frame

The validation of the data acquired was done by fixing the IMU in a rotating bench seen in “Figure 7a” vise and comparing the last 100 measures average to a manual goniometer measure as shown in “Figure 7b”.



Figure 7. Inertial Measurement Unit Tests

Firstly, a neutral position was tested, which in this case corresponded to the positive Z axis oriented with the gravity force, while the others two axes had an orthogonal orientation with the gravity. Four rotations about the X and Y axes were done, being two of them in the positive direction and the other two in the negative direction of each one of the axes (eight rotations in total). Another four rotations were done by combining the rotations in the two axes (X and Y) and encompassing every four possibilities (positive direction in the Y axis with negative and positive direction of X axis and negative direction in the Y axis with negative and positive direction of X axis). The tests results in degrees are presented in Table 2, while in Table 3 it is possible to visualize the measured error in degrees and in percentage.

Table 2. Degrees Measurement Obtained During IMU Testing

Orientation	Expected (°)			Obtained (°)		
	X	Y	Z	X	Y	Z
Neutral	90.00	90.00	180.00	85.75	88.51	175.47
Y axis Rotation	74.00	90.00	164.00	70.81	88.30	160.71
	66.00	90.00	156.00	63.38	88.79	153.33
	115.00	90.00	155.00	110.98	88.97	159.02
	126.00	90.00	144.00	121.53	88.12	148.43
X axis Rotation	90.00	104.00	166.00	87.66	101.69	168.09
	90.00	116.00	154.00	85.78	115.45	154.18
	90.00	74.00	164.00	87.47	73.48	163.26
	90.00	58.00	148.00	87.73	58.13	148.01
Y and X Combined Rotation	74.00	123.00	162.00	72.47	121.37	143.12
	108.00	129.00	141.00	103.39	128.08	138.83
	82.00	68.00	158.00	75.01	67.75	152.68
	110.00	43.00	133.00	100.37	42.52	130.65

Table 3. Error Measurement Obtained During IMU Testing

Orientation	Error (°)			Error (%)		
	X	Y	Z	X	Y	Z
Neutral	-4.25	-1.49	-4.53	-4.72%	-1.66%	-2.52%
Y axis Rotation	-3.19	-1.70	-3.29	-4.31%	-1.89%	-2.01%
	-2.62	-1.21	-2.67	-3.97%	-1.34%	-1.71%
	-4.02	-1.03	4.02	-3.50%	-1.14%	2.59%
	-4.47	-1.88	4.43	-3.55%	-2.09%	3.08%
X axis Rotation	-2.34	-2.31	2.09	-2.60%	-2.22%	1.26%
	-4.22	-0.55	0.18	-4.69%	-0.47%	0.12%
	-2.53	-0.52	-0.74	-2.81%	-0.70%	-0.45%
	-2.27	0.13	0.01	-2.52%	0.22%	0.01%
Y and X Combined Rotation	-1.53	-1.63	-18.88	-2.07%	-1.33%	-11.65%
	-4.61	-0.92	-2.17	-4.27%	-0.71%	-1.54%
	-6.99	-0.25	-5.32	-8.52%	-0.37%	-3.37%
	-9.63	-0.48	-2.35	-8.75%	-1.12%	-1.77%

After embedding the IMU in the IO, the same tests were repeated comparing the measure acquired from the sensor with the goniometer measure seen in “Figure 8a” and the difference was the axis aligned with the gravity force, that instead of the Z axis was the Y axis, consequently the rotations were done about the Z and X axes as is possible to observe in “Figure 8b”.

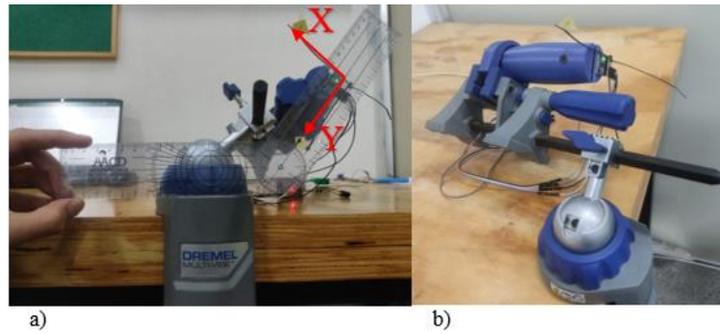


Figure 8. Inertial Measurement Unit Embedded in the IO Tests

The results are presented below, where Table 4 shows the expected and the obtained measures in degrees, while in Table 5 can be seen the errors measured in degrees and in percentage.

Table 4. Degrees Measurement Obtained with the IMU Embedded in the IO

Orientation	Expected (°)			Obtained (°)		
	X	Y	Z	X	Y	Z
Neutral	90.00	180.00	90.00	90.35	179.24	90.71
Z axis Rotation	79.00	169.00	90.00	79.02	169.02	89.79
	52.00	142.00	91.00	50.97	140.95	91.03
	119.00	151.00	90.00	120.78	149.25	88.95
	155.00	115.00	90.00	155.63	114.42	89.53
X axis Rotation	90.00	162.00	72.00	88.61	159.08	69.11
	90.00	157.00	67.00	88.75	154.19	64.20
	90.00	163.00	107.00	88.87	164.02	105.96
	90.00	142.00	128.00	89.03	141.86	128.15
Z and X Combined Rotation	129.00	141.00	72.00	132.79	131.13	70.94
	62.00	152.00	75.00	66.97	148.58	69.83
	132.00	138.00	115.00	134.78	125.34	114.36
	60.00	150.00	120.00	63.91	140.15	117.79

Table 5. Error Measurement Obtained with the IMU Embedded in the IO

Orientation	Error (°)			Erro (%)		
	X	Y	Z	X	Y	Z
Neutral	0.35	-0.76	0.71	0.39%	-0.42%	0.79%
Y axis Rotation	0.02	0.02	-0.21	0.03%	0.01%	-0.23%
	-1.03	-1.05	0.03	-1.98%	-0.74%	0.03%
	1.78	-1.75	-1.05	1.50%	-1.16%	-1.17%
	0.63	-0.58	-0.47	0.41%	-0.50%	-0.52%
X axis Rotation	-1.39	-2.92	-2.89	-1.54%	-1.80%	-4.01%
	-1.25	-2.81	-2.80	-1.39%	-1.79%	-4.18%
	-1.13	1.02	-1.04	-1.26%	0.63%	-0.97%
	-0.97	-0.14	0.15	-1.08%	-0.10%	0.12%
Y and X Combined Rotation	3.79	-9.87	-1.06	2.94%	-7.00%	-1.47%
	4.97	-3.42	-5.17	8.02%	-2.25%	-6.89%
	2.78	-12.66	-0.64	2.11%	-9.17%	-0.56%
	3.91	-9.85	-2.21	6.52%	-6.57%	-1.84%

2.4 IoT Nodes

The final prototype consists in an Internet of Things device, which it is capable of sending the data acquired from both sensors to a *Web Application* through *Message Queuing Telemetry Transport* (MQTT) protocol. The measurements interpreted by the μC are converted in a JSON message and published in a local Mosquitto MQTT broker using the PubSubClient Arduino library. The *Web Application* subscribes to the information published by the IO and updates it on the dashboard. The dashboard was developed using Node-Red and displays the real time measurements of orientation and force that is being applied on the Object as well as historical charts with the last 30 minutes measures as can be seen in Figure 9.

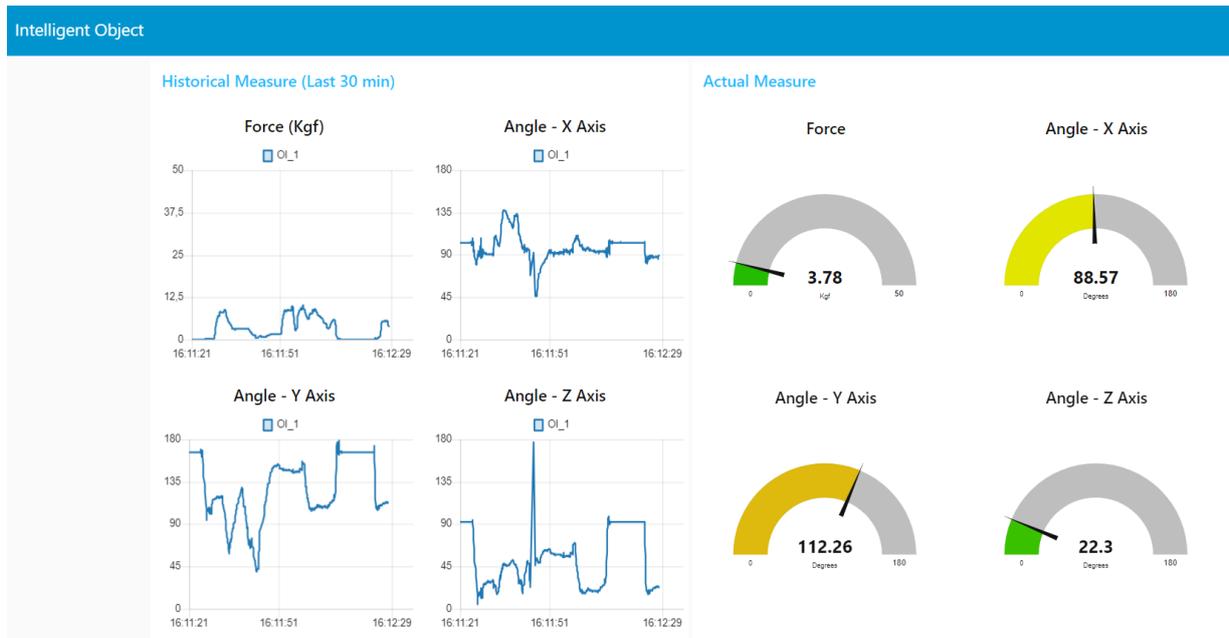


Figure 9. Developed Dashboard

2.5 Orientation Test

The tests were carried out by the laboratory researchers. Three different positions were tried, as presented in Figure 10. In the first position, the forearm is not rotated, therefore, it is not being performed neither pronation nor supination, what does not happen in the second position, where forearm pronation is being performed. In the third position a wrist adduction, also called ulnar deviation of the hand, is being performed. In all positions the IO is kept grasped and its orientation is being measured.



Figure 10. Example Test with a Human Hand

The orientation measurements acquired during the example tests can be analyzed in Figure 11. The dark blue line is the angle with the X axis, the light blue line is the angle with the Y axis and the orange line is the angle with the Z axis. The first position measurements are represented after the first black line until the second light green line. The second position measurements are shown after the second black line until the third light green line. The last position measurements are visible after the third black line until the end of the chart. The areas after the light green vertical line until the black vertical lines represent the transition movements to get from one position to the other.

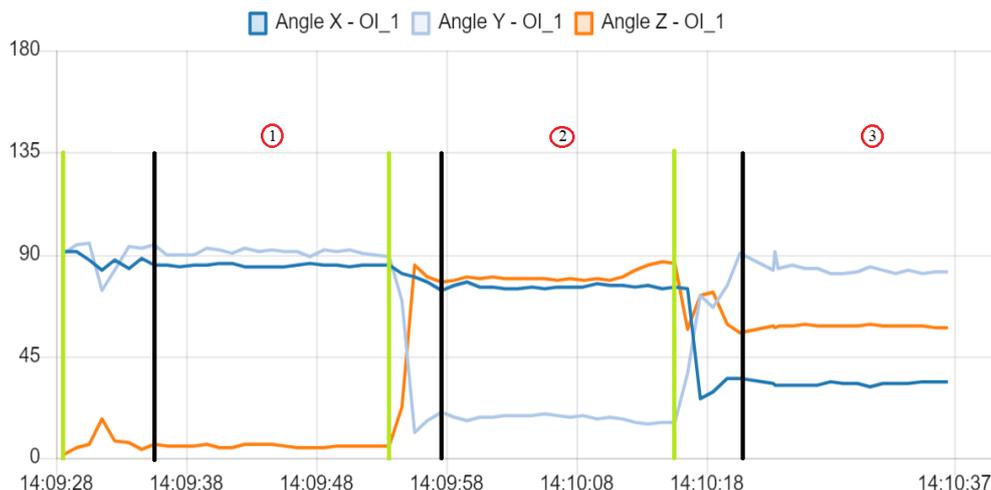


Figure 11. Orientation Test Results

3. DISCUSSIONS AND CONCLUSIONS

The achieved results presented in the previous section demonstrate that the Intelligent Object was able to provide information about its orientation and the applied force on it. Analyzing the load cell obtained errors, it is perceivable that the measurements are accurate, consequently the adjustments were done correctly. The maximum percentual error was nearly 1%, which is adequate for the proposed application. The IMU measurements were also accurate when rotation is performed in a single axis. Considering this condition, in both IMU tests (embedded or not in the IO), the error did not reach a value higher than 5% and it is also adequate in the context of this work. However, during the combined rotation tests, the error reached 11.65% without the IMU being embedded in the IO and 9.27% when the IMU was embedded in the IO. Comparing the results between the tests with single axis rotation error and the combined rotation error, it is notable that the second is higher than the first, probably due to the offset adjustment procedure, which takes into account the axis measurements separately. Hence, improvements could be done in this direction.

The ESP32 microcontroller was able to send the measured data to the developed dashboard using the *Message Queuing Telemetry Transport* protocol. The *Node Red Web Application* presents the historical and real time measurements correctly, and in a user-friendly manner. Thus, it is feasible that a rehabilitation specialist could use the acquired data to analyze the patient's situation and, therefore, create an appropriate prostheses training strategy.

The aim of this work was accomplished once that the Intelligent Object was designed and developed in a proper manner. The obtained results look promising once they showed that the use of the proposed instrument is feasible and it is able to provide useful information that allows the therapist to create an upper limb measurable prosthesis training strategy to enhance patient's adherence to rehabilitation, for example. Even though, improvements to the IMU measurements are ongoing. In order to prove if this approach is really going to lead a useful new upper limb prosthesis training protocol, the next step is to test it in patients.

4. ACKNOWLEDGEMENTS

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