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Design and testing of a sensor-based prototype for measuring the cognitive status through finger force modulation

Nicole Morresi[1], Giuseppe Pandarese[1], Roberta Bevilacqua[2], Gian Marco Revel[1], Sara Casaccia[1]

[1] *Department of Industrial Engineering and Mathematical Sciences, Università Politecnica delle Marche , Via Brecce Bianche 12, 60131 Ancona, Italy*
[2] *Scientific Direction, IRCCS INRCA, 60124 Ancona, Italy*

ABSTRACT
This study presents a preliminary prototype of a sensor-based system for assessing cognitive status through finger force modulation. The system integrates strain-gauge load cells within a game-like interface, prompting users to apply and maintain specific force levels using their index finger. The resulting force-time profiles are analyzed and compared to a template curve, using Dynamic Time Warping (DTW) and Partial Curve Mapping (PCM), generating a Similarity Index (SI) that quantifies task accuracy. A thresholding system classifies participants into cognitive status levels (High, Medium, Low). The sensing platform was calibrated using standard weights to ensure reliable force measurement. The prototype was tested on 24 participants (16 young adults and 8 seniors) and results showed that PCM outperforms DTW with the 80 % of young adults achieved a "High" cognitive status, while among seniors, 79 % were classified as "Medium" and 6 % as "Low". These findings confirm that age-related motor variability can reflect underlying cognitive differences. The proposed system demonstrates potential for non-invasive, remote cognitive assessment and supports future development of digital tools for aging populations and individuals diagnosed with Mild Cognitive Impairment (MCI) or dementia (PwD).

Section: RESEARCH PAPER

Keywords: Mild cognitive impairment; force measurement; load cells; cognitive training

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Corresponding author: Nicole Morres, e-mail: n.morresi@pm.univpm.it

1. INTRODUCTION

The ability to measure and quantify the cognitive status of seniors is becoming a growing global priority, particularly for individuals diagnosed with Mild Cognitive Impairment (MCI) or dementia (PwD). Accurate and timely evaluation of cognitive function is essential for guiding care strategies and improving the quality of interventions, ultimately enhancing the overall well-being of older adults [1]-[3]. This challenge is even more justified by the increasing demands placed on formal and informal caregivers, who often face emotional, physical, and financial burdens. In this context, tools that enable earlier detection and continuous monitoring are not only clinically valuable but also socially imperative [1].

Conventional cognitive screening tools, such as the Mini-Mental State Examination (MMSE) and the Montreal Cognitive Assessment (MoCA), remain the gold standard in clinical practice [2]. However, these assessments have several inherent limitations. They require professional administration, are subject to inter-rater variability, and do not support real-time or continuous monitoring. Furthermore, they often rely on sensitive and abstract questioning that can induce anxiety or discomfort in older individuals, affecting performance and complicating interpretation [3], [4]. This further emphasizes the need for intuitive, user-friendly tools that can support clinicians with objective, complementary data for diagnostic decision-making. These limitations underscore the need for approaches that are both objective and user-friendly.

To address these gaps, current research is focusing on technology-enabled cognitive assessment and training solutions for optimizing the quality of care and prioritizing patients. The rise of sensor-based platforms and digital therapeutic interventions, delivered via mobile, wearable, or home-based systems—offers a pathway toward scalable and minimally intrusive cognitive monitoring. The ability to unobtrusively monitor cognitive status outside of clinical settings through telemonitoring devices would enable more timely interventions and relieve part of the monitoring responsibility currently placed on caregivers [5], [6]. This highlights the growing necessity for remote, real-time assessment tools that are scalable, interpretable, and capable of providing continuous cognitive monitoring. These systems have the potential to combine engagement with clinical utility, offering the possibility of long-term cognitive training, early anomaly detection, and reduced caregiver burden. However, to guarantee widespread adoption depends on designing tools that are not only accurate and clinically meaningful but also intuitive and integrated into users' daily routines.

In this context, this research presents a prototype of a sensor-based system that aims to assess cognitive status of seniors through finger force modulation. The device leverages a game-based interface to engage participants in applying and maintaining a target force using their index finger. Force patterns are analysed using Dynamic Time Warping (DTW) and Partial Curve Mapping (PCM), producing a Similarity Index (SI) that reflects the user's ability to modulate fine motor control, which literature recognizes as an indirect indicator of cognitive function [7]-[9]. The system is designed to be non-invasive, easily deployable, and supportive of remote or in-clinic use. This prototype does not replace formal diagnostic tools but acts as a foundation for developing scalable, technology-driven screening measurement systems to be used in non-clinical settings. Moreover, although previous studies have investigated finger force control in aging and clinical populations, no suitable accessible datasets were available that matched the requirements of this experimental design, therefore a dedicated data collection process was necessary to ensure consistency. The proposed work introduces a preliminary version of a force-sensing device, designed to determine whether age-related differences in motor function can be objectively measured through force modulation tasks. The assumption is that, as suggested by existing research, motor function deteriorates with age, and this decline may serve as an indicator of cognitive impairment.

The remainder of this paper is structured as follows: Section 2 presents a detailed review of current sensor-based cognitive assessment technologies and finger-based motor evaluation tools. Section 3 describes the architecture of the proposed system, including sensor calibration procedures, task design, and signal analysis methodology. Section 4 reports experimental findings comparing performance across different age groups. Finally, Section 5 concludes the paper with key observations, implications, and directions for future development. This work is also framed within the broader vision of the HAAL ("Healthy Ageing eco-system for people with dementia") project, which aims to integrate multimodal sensors - including force-based interaction modules - into a comprehensive digital health ecosystem for PwD monitoring and care support.

2. STATE OF THE ART

Recent research in the field has expressed increasing interest in sensor-based measurement system for evaluating cognitive status, given the need for objective, scalable, and non-invasive monitoring tools. A wide range of methodologies have been explored, including gait analysis, hand tremor detection, electroencephalography (EEG), and wearable physiological monitoring [7], [8]. These approaches aim to go beyond traditional questionnaire-based assessments since their goal is to capture neurophysiological or behavioral data that correlates with cognitive function. Among these, finger-based force modulation tasks have emerged as particularly promising, offering a high-resolution view into domains such as executive functioning, attention regulation, and working memory, all of which are related to early cognitive decline[9], [10].

The relationship between motor performance and cognitive decline is well-established in literature. Neuromechanical and neurodegenerative research shows that motor impairments, particularly in fine motor control, often co-occur with cognitive dysfunction in aging populations. Tasks involving sustained grip, tapping, and trajectory following have demonstrated sensitivity to changes in cognitive state. While gross motor features like gait variability are commonly used in early dementia detection, recent evidence highlights that fine motor tasks, such as those involving force precision and modulation, may capture more subtle signs of decline and are easier to administer in compact or wearable design.

Finger-based exercises embedded in these platforms target executive functioning and working memory while allowing quantifiable performance tracking. Current studies highlight the diagnostic potential of finger-based motor assessments when paired with high-resolution sensors and robust analytical methods. For example, [10] developed a home rehabilitation system that assesses finger independence using pressure sensors and applies Dynamic Time Warping (DTW) to compare force curves against normative templates. [11] used magnetic sensors to evaluate tapping behavior in elderly subjects, finding that greater motor irregularities correlated with MMSE scores. Despite the potential of these systems, the field currently lacks a standardized, quantitative framework for assessing cognitive status through finger force modulation. Many tools rely on qualitative assessments or time-based metrics, which are susceptible to noise. Moreover, while gamified systems are increasingly popular, few incorporate advanced signal analysis techniques or real-time feedback mechanisms that could enhance clinical confidence and interpretability [12], [13]. Existing systems also often fail to account for device calibration or measurement uncertainty, which are critical factors when transitioning from experimental prototypes to clinical deployment.

To analyze force or pressure profiles, literature presents different strategies that include also the application of DTW, which is a well-established algorithm for comparing time-dependent trajectories, widely used in rehabilitation and movement analysis [14]. In the cognitive domain, DTW has been used to evaluate motor performance in elderly individuals, distinguish between healthy and cognitively impaired participants, and profile functional recovery in stroke and Parkinson's disease [15]. In parallel, Partial Curve Mapping (PCM), though less prevalent in literature under a standardized definition, draws on similar principles of shape-based alignment. PCM focuses on morphological similarity rather than time alignment, offering complementary insight into the structural fidelity of force application patterns [16].

To address the limitations outlined above, this study proposes a game-based, sensor-integrated prototype that quantifies cognitive performance through finger force modulation. By embedding strain-gauge load cells into an interactive task and analyzing the resulting force trajectories using DTW and PCM, the system generates an objective

Similarity Index (SI) which is further interpreted via a thresholding system to enable cognitive status classification. Unlike traditional assessments, this approach fosters user engagement, offers real-time feedback, and supports remote or clinical use.

3. MATERIALS AND METHODS

In this research, the prototype for the measurement of users' cognitive status relies on the use of force sensors embedded in a finger-based interaction platform, where participants perform targeted force control exercises. Specifically, users are instructed to apply a specific force on a dedicated support and maintain it constant for a pre-defined time interval. The resulting force curve is recorded in real time using a data acquisition unit (DAQ) and analysed. Signal processing techniques are used to compare the user's force trajectory with an ideal template, yielding to a SI. This index quantifies the user's ability to modulate and sustain force and is interpreted through a thresholding system that classifies performance into cognitive status levels (e.g., high, medium, low). The proposed system, developed as a non-invasive and scalable prototype, aims to support objective cognitive evaluation, particularly in aging populations.

3.1. Measurement set-up

A load cell has been developed, consisting of a thin steel sheet, whose technical characteristics are listed in Table 1. The thin sheet has two holes with a diameter of 3 mm, one of which is used for anchoring to the provided support, and the other is used as a marker for applying force. To derive the applied force from the deformation of the sheet, two strain gauges (Table 1) with a half-bridge configuration have been installed. The thin steel sheet was fixed on a 3D-printed dedicated support to facilitate the application of the force from the participant (Figure 1).

Table 1. Technical characteristics of each component of the proposed measurement system.

Components	Characteristics
Steel sheet	Material: AISI 302 Young's Modulus: 193 GPa Length: 31 mm Width: 8 mm Thickness: 1 mm
Strain gauge	Constructor: Hottinger Baldwin Messtechnik *R* = 120 Ohm Gauge Factor *k* = 2.02

Figure 1. The thin steel placed on the dedicated support. On one extremity of the thin sheet there is the 3D-printed dedicated point of application of the force.

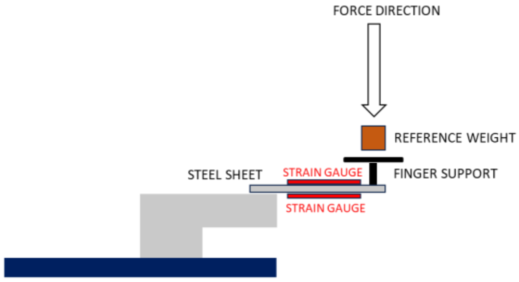


Figure 2. Set-up for performing the calibration with known weights.

3.2. Metrological characterization of the load cell

In this section, the calibration of the sensor is introduced considered both from a static and dynamic perspective. In both cases, to obtain the data from the load cell, a National Instrument data acquisition (DAQ) device (NI USB X series 6356, National Instruments) is used to acquire the deformation using Labview. The data acquisition system is connected to the load cells and the applied curve is recorded from the system; after the data collection, the analysis is then performed through Python programming language.

The measurement uncertainty of the sensor is assessed at different level of deformation. To calibrate the force sensor, the experimental setup showed in Figure. 2 is used; the calibration is performed by applying a known weight while measuring the corresponding displacement, in the range of loads that are comprised in the desired measurement range [17]. The range of loads applied, selected according to existing literature, is from 26 g to 1027 g (equal to 0.25-10 N), with intermediate steps of 50 g, repeating the procedure four times for each weight [18]; for each load applied, the corresponding deformation is recorded. The result of the process is displayed in Figure 3, where the applied weight is plotted against the corresponding deformation, as well as the linear regression line. The Type A measurement uncertainty of the calibration was then computed, which is 4.8 % considering a coverage factor k = 2, while the sensitivity of the system K is equal to 0.64 [19].

In addition, the load cell was also characterized from a dynamic perspective, by applying a standard input signal using a shock hammer, which is the impulse signal offering insights into transient behaviour of the load cell [20]. This procedure served as validation step to ensure that the sensor would not introduce

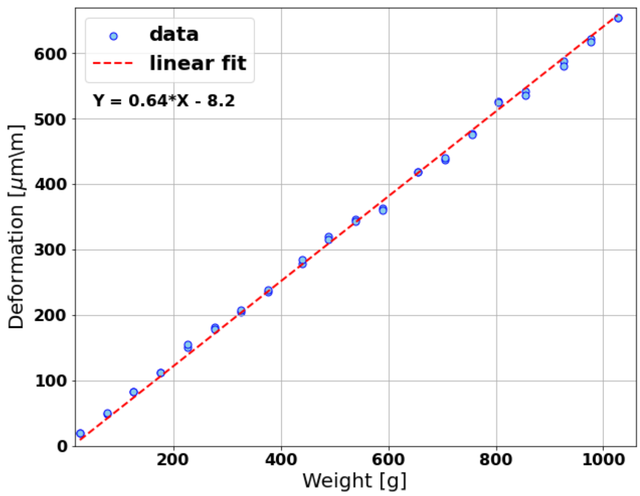


Figure 3. Results of the calibration and related curve fitting.

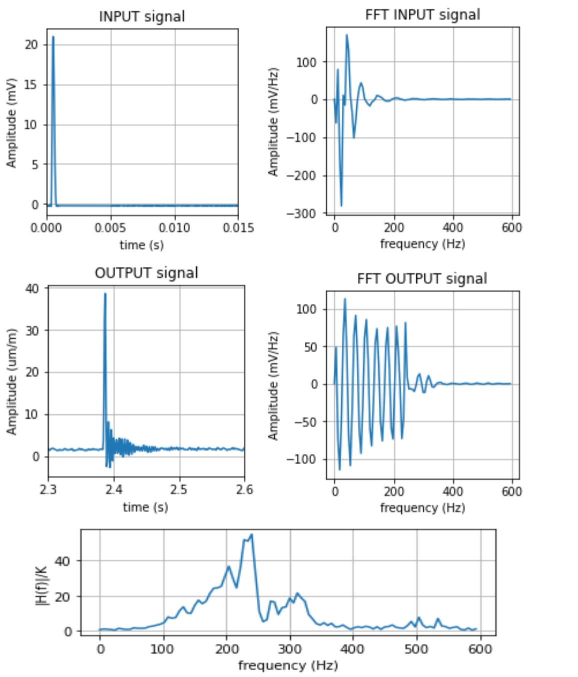


Figure 4. Signals acquired for analysing the dynamic response of the load cell. Upper left: input impulse signal. Upper right: FFT of the input signal. Lower left: output signal recorded from the load cell. Lower right: FFT of the output signal. Lower centre: magnitude of the frequency response.

distortions or attenuate the signal during the force modulation task. The response of the load cell was sampled at 1200 Hz to analyse its full frequency spectrum, considering that the operational sampling frequency is 100 Hz. The magnitude of the frequency response is displayed in Figure 4 showing that for frequency below 80 Hz the magnitude normalized to the sensitivity K is 1.

3.3. Measurement procedure

The evaluation of users' cognitive state occurs by assessing their ability to control the force applied by their fingers; therefore, the purpose of the test is to quantitatively assess how users perform a predefined task by applying a known deformation, for a defined time interval. The experimental procedure requires participants to exert a specific force on the dedicated support and maintain it constant for 10 seconds (Figure 5). This procedure is selected according to literature findings, in which it is reported that Sustained force tasks have been widely employed in cognitive-motor research as they provide sensitive measures of fine motor control, fatigue, and cognitive integration [21], [22] . At the beginning of the test, users position themselves at the test bench and place the palm of their preferred hand on the dedicated support, with the index

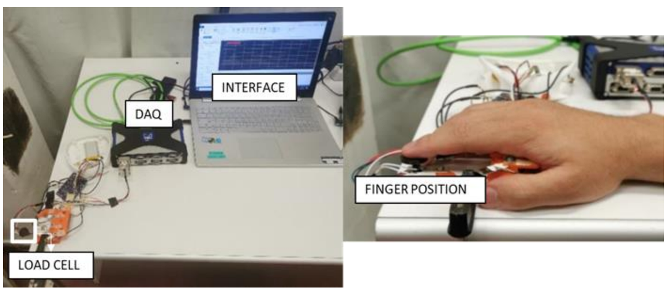


Figure 5. Experimental set-up.

finger resting on the 3D- printed support, correctly positioned at the force application point. To ensure the consistency of the tests all participants placed the hand in the same position.

The tests are always supervised by attendants who, besides instructing the participants on the correct procedure and initiating data acquisition, ensure that all instructions are followed. Each user performs three trials applying weights 321 g (3.14 N), 475 g (4.65 N), and 783 g (7.7 N), which result in deformations of the load cell of 200 μm/mm, 300 μm/mm, 500 μm/mm respectively. Once the required deformation for each trial is reached, the participant must maintain constant force for 10 s. After completing 3 trials, participants must repeat them for a second time, completing a total of 6 trials, each lasting 10 seconds. Participants can see in real-time the applied deformation from the software interface where a graph illustrates real-time deformation in μm/mm on the y-axis and time in seconds on the x-axis and shows the desired level of deformation to be applied. The target provided to the users is the deformation they must achieve in each trial. Before commencing the trials, each participant was given the opportunity to familiarize themselves with the device by conducting a test, applying varying intensities, and observing the corresponding deformation. They also filled out the informed consent form and were provided with an explanation about the purpose of the experiment (e. g., developing a method to measure the cognitive state of older people).

3.4. Participants

To test the proposed solution, the sensor was tested on a total of 24 participants belonging to two different groups [13] . Firstly, 17 healthy young adults (9 females and 8 males, age < 65 y) were voluntarily recruited, with an average age of 25 ± 3 years; this experiment was conducted in the laboratory environment of Università Politecnica delle Marche. Secondly the solution was tested by 8 voluntarily recruited seniors (3 females, 5 males, age > 65 years old, with an average age of 90 ± 3 years), at the IRCCS INRCA hospital. This sample size is consistent with recent studies in the field, where early-stage feasibility evaluations with older adults have used similar participant numbers [23], [24]. This group of seniors was selected since studies have shown that cognitive decline accelerates in individuals over 80 years of age [25] All the participants gave information to use their personal data.

3.5. Data analysis

To quantitatively assess the users' cognitive state, two different algorithms selected from the literature were used: PCM and DTW. These algorithms were selected to determine the proper method for analysing the force curves obtained from participants during the cognitive training exercise: the algorithms are used to compare and analyse the force curve obtained from the participant, against a template.

PCM is a methodology used to compute the match between two arbitrary curves [16], [26]. It is an algorithm that calculates the misalignment and lack of correspondence between two curves through the area between the two considered curves. The measurement has a lower limit of zero when two curves are identical (exact correspondence), while the greater the measurement, the more distant the curves are. PCM is particularly useful for capturing the overall shape and trend of the curves, making it a robust choice for the scope of this research. The DTW is an algorithm that allows alignment between two temporal sequences of different lengths by

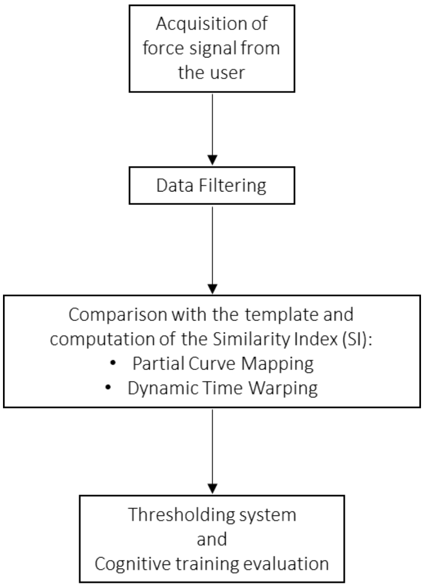


Figure 6. Flowchart of the data processing for the evaluation and measurement of the cognitive training.

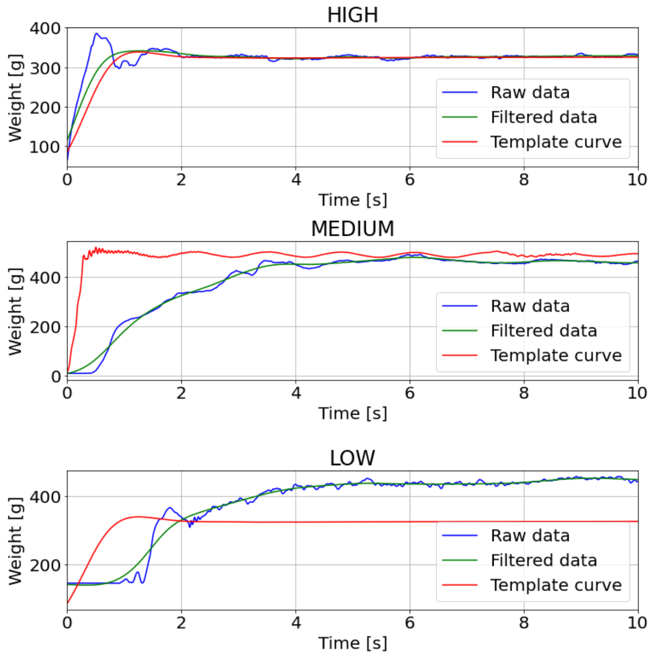


Figure 7. Example of template (in red) against raw data and filtered data obtained to derive the thresholding system, using the PCM algorithm; in this example the algorithm provided a SI of 21, 130, 234 for the class HIGH, MEDIUM and LOW respectively.

exploiting temporal distortion and measures the distance between the two aligned sequences [27]. In this case as well, a null value is obtained for identical sequences (zero distance between points), and the values increase as the distance between the sequences increases. Both PCM and DTW were chosen and compared to evaluate which algorithm best aligns with the objective of this research, despite their slight differences: PCM is more suitable at comparing overall trends, while DTW is preferable in matching temporal variations.

After selecting the algorithms, the data processing flow is reported in Figure 6. Specifically, these two algorithms are used to compare the force curve obtained from the participant to an ideal template. Consequently, if the force curve and the template have a similar trend and are nearly or fully overlapping, it is assumed that the user performed the task properly indicating a higher cognitive state. Conversely, if they have different trends and are not overlapping, it is assumed that the user did not perform the task in a proper manner, resulting in a decreased cognitive state and a necessity of more training. In terms of computing performances, average per-trial computation time was approximately 18 ms for DTW and under 5 ms for PCM, confirming the greater suitability of PCM for real-time or embedded applications.

After the acquisition of the raw force signal (Figure 7) from the participant, the raw signal is filtered using a Butterworth filter (fc = 0.01 Hz, $filter\_order$ = 2), to remove unwanted oscillations while preserving the morphological structure of the signal relevant for the analysis [28]. Then, the filtered signal is compared with the template PCM and DTW, to obtain the SI.

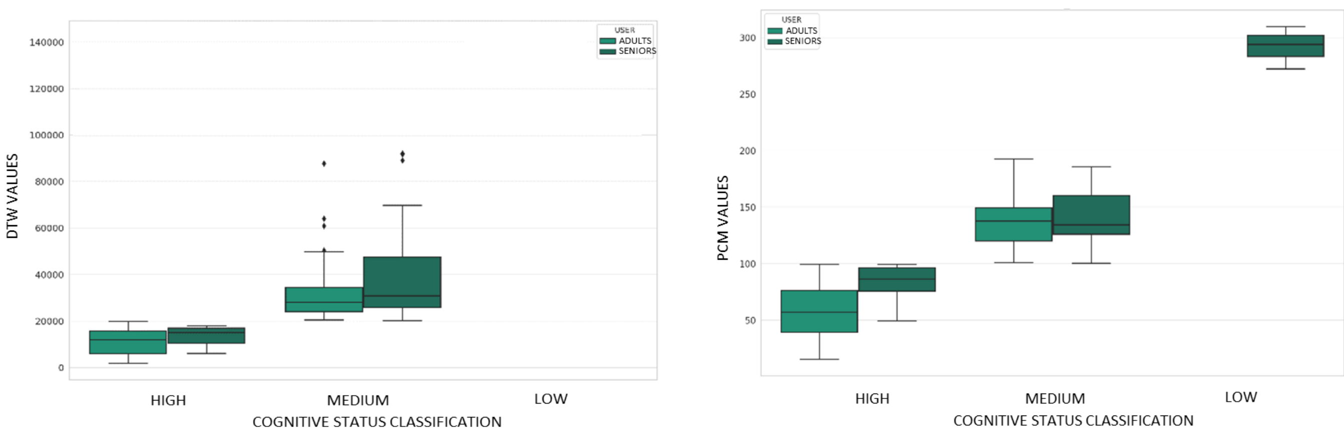
To derive a quantitative index, a thresholding method already present in literature was used to classify the SI into three classes: High, Medium and Low [29]. The range of values to classify the computed SI was computed empirically: the category High was retrieved by computing the SI between two completely overlapping curves, while the category Low was identified by computing the SI between two curves that do not overlap (Table 2). In clinical practice, it is expected that older adults will generally exhibit lower SI values due to the physiological aging, reflecting their expected reduced cognitive capabilities. This expectation aligns with established findings that cognitive decline is common in aging populations and those with MCI [30], [31]. Example of curves associated to each class Low, Medium, and High are reported in Figure 7, obtained from the experiments. After computing the SI, the thresholding system derives the level of cognitive training, according to the similarity between the template and the curve obtained from the experiment conducted by the different participants.

Table 2. Thresholding systems for classifying the similarity indices PCM and DTW into Low, Medium and High.

Class	Threshold for PCM	Threshold for DTW
Low	229 < *PCM* < 730	255001 < *DTW* < 75500
Medium	101 < *PCM* < 228	20001 < *DTW* < 255000
High	0 < *PCM* < 100	0 < *DTW* < 20000

4. RESULTS

The results of the SI, computed with PCM and DTW, for the experiment conducted are displayed Figure 8. Figure 8a shows the result of the SI obtained by applying the PCM algorithms, grouped for each category of participants (young adults and seniors). Figure 8b displays the result of the application of the DTW to calculate the SI. First, to verify the hypotheses that there are significant differences among the experiment conducted by the two classes of adults and seniors, the t-test was conducted, with a 95 % of significance [32], [33]. The test reveals that the group (young adults or seniors) significantly affect both the PCM and DTW values, with p-value < 0.05 and t-statistics of -8.7 and -3, respectively. Table 3 reports the percentage of trials classified as High, Medium, and Low for both young adults and seniors. It is evident that the High classification, indicating a high cognitive status, is



(a) (b)

Figure 8. Plot of the results of the thresholding system, grouped by participant (young adults or seniors), against the related class for the cognitive training for the PCM (a) and DTW (b).

Table 3. Percentage of participants - adults (A) or seniors (S) - that were classified as High, Medium and Low from the application of the thresholding system.

Algorithm	High		Medium		Low	
	A	S	A	S	A	S
PCM	80 %	15 %	20 %	79 %	0 %	6 %
DTW	49 %	19 %	51 %	81 %	0 %	0 %

predominantly obtained during the experiments with young adults. Conversely, the “Medium” classification is more common among seniors, while the Low classification is only present in the seniors' trials. The results indicate a clear distinction between the cognitive performance of young adults and seniors. Using PCM, 80 % of young adults achieved a High cognitive status, compared to only 15 % of seniors. This suggests that young adults are more likely to maintain force control like the ideal template, reflecting their higher cognitive capabilities. In contrast, 79 % of seniors were classified as Medium using PCM, highlighting that most seniors exhibit moderate alignment with the template force profile. Additionally, a small percentage (6 %) of seniors were classified as Low from PCM indicating significant deviation from the template and suggesting lower cognitive performance. The absence of "Low" classifications detected by the DTW, which is less sensitive than the PCM, since DTW is primarily designed to compensate for temporal misalignments between curves, while PCM is more responsive to shape discrepancies. The DTW results show a similar trend, with 49 % of young adults classified as "High" and 19 % of seniors achieving the same status. Most seniors (81 %) fell into the Medium category, while no participants were classified as Low using DTW. This further underscores the trend that seniors generally exhibit lower cognitive performance compared to young adults. Overall, both PCM and DTW effectively differentiate between the cognitive status of young adults and seniors, with PCM providing slightly more granularity in distinguishing Low cognitive status among seniors. It is less sensitive to small temporal misalignments, making it effective in capturing the general pattern of the force application. This characteristic makes PCM suitable for assessing the overall trend but less effective in capturing precise temporal distortions.

5. CONCLUSION

The goal of this research is based on the need to include games for cognitive training of MCI and PwD and provide a real-time instrument for supporting clinician in the remote monitoring of users at home. A prototype utilizing finger-based games for cognitive enhancement was developed, leveraging strain-gauge load cell technology, prior system calibration. Participants are required to exert a specified force over a set duration, with the exerted force profile being subsequently compared to a standard curve.

The calibration of the sensor was performed to ensure the accuracy and reliability of the force measurements. This process enabled the generation of precise data, significantly influencing the decision-making process for caregivers and health professionals. By providing a dependable measure of cognitive function, the calibrated system empowers these professionals to make informed decisions regarding the design and adjustment of cognitive training protocols, potentially leading to more personalized and effective care strategies.

The similarity between the participant's force profile and the template is assessed using PCM and DTW algorithms, which serves as a basis for categorizing cognitive status into distinct classifications. The result is promising as the prototype aimed at investigating whether in different population (adults and seniors) variations in motor performance can be objectively captured through controlled force modulation tasks. Having assumptions from existing literature, the underlying hypothesis is that motor function tends to decline with age, and such changes may offer valuable insights into cognitive status, particularly in the context of early detection of impairment, and this is confirmed with this prototype. Initial system calibration was followed by evaluations with two distinct demographic groups: young adults and seniors. This study highlights the potential of the proposed measurement system as an effective tool for cognitive assessment and remote monitoring. The integration of force sensors and advanced algorithms like PCM and DTW provides a reliable, real-time method to evaluate cognitive status, offering significant implications for clinical practices in cognitive health assessment and management. The system not only demonstrates the capability to distinguish cognitive status across varied age groups but also holds promise for enhancing the quality of life for individuals with cognitive impairments through targeted intervention strategies.

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