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Gamified Motor Learning Through High-Fidelity Sensor Technology

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***Abstract*—In this paper, we present a framework for gamified motor learning through the use of a serious game and high-fidelity motion capture sensors. Our implementation features an Inertial Measurement Unit and a set of Force Plates in order to obtain real-time, high-frequency measurements of patients' core movements and centre of pressure displacement during physical rehabilitation sessions. The aforementioned signals enable two mechanisms, namely a) a game avatar controlled through patient motor skills and b) a rich data stream for post-game motor performance analysis. Our main contribution is a fine-grained processing pipeline for sensor signals, enabling the extraction of a reliable and accurate mapping between patient motor movements, in-game avatar controls and overall motor performance. Moreover, we discuss the potential of this framework towards the implementation of personalised therapeutic sessions and present a pilot study conducted in that direction.**

***Index Terms*—Motor learning, gamification, physical rehabilitation, motion sensors**

I. Introduction

The gamification of therapeutic processes is a powerful tool that can have both social and motivational advantages [1]. In recent years, a multitude of studies have discussed gamified applications for physical rehabilitation. These applications are fed with kinematic features that are captured through modern, cost-effective motion capture technologies such as Microsoft Kinect [2], [3], Nintendo Wii [4], Google MediaPipe [5], [6] and OpenPose [7]. Despite the advantages the aforementioned technologies yield, such as cost efficiency and ease of use, they come with a major limitation: a noticeable pose detection error margin [8], [9]. While this does not necessarily hinder their use as alternative game controllers, it is likely to lead to unreliable and noisy kinematic signals. In both short- and long-term analysis of gamified treatment outcomes, inaccurate measurements can lead to erroneous diagnoses and false therapeutic evaluations. To address such issues, games controlled by kinetic signals such as force distribution and regulation or Centre of Pressure (COP) displacement have been implemented [10], [11]. Yet an integration of both of these signals as a game controller and performance analysis channel is, to our knowledge, sparse in scientific literature.

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In this paper, we present a framework towards the gamification of motor learning through high-fidelity motion sensor and force plates technology. We propose a novel system which not only focuses on multiple motor skills, but also produces high-accuracy, analysis-ready kinematic and kinetic data. More specifically, we implemented a 3D game where the player's goal is to fly through targets which have predefined positions in a 2D coordinate system. Depending on the therapeutic goals, the airplane can be controlled both through trunk rotations or COP displacement using high-frequency Inertial Measurement Units (IMUs) (500Hz) and Force Plates (FPs) (200Hz) respectively. The selected set of sensors enables both reliable real-time game avatar control and accurate post-session kinematic and COP analysis.

Through the proposed framework, we enable high-fidelity longitudinal studies of motor learning performance. Our goal is to provide gamified spaces that can be used as a supplement for traditional physical rehabilitation. To that end, the current study mostly focuses on the analysis of the kinematic and kinetic signals and less so on the game design. However, we designed our system to be highly adaptable; regardless of the game's nature and design, a robust analysis of kinematic or kinetic behaviour ensures that the therapeutic procedure can reach reliable conclusions.

II. Related Work

A. Games for Motor Learning

As far as motor learning is considered, there is a wide variety of games, sensors and assessment protocols that can be found in literature. A large part of previous research has studied motor skill learning and motor adaptation of those skills in different conditions in healthy adults, in laboratory settings. In rehabilitation, we assume that these principles will apply to patients that need to relearn specific movements [12]. However, every patient and condition differs, meaning that personalised rehabilitation is necessary. For example, some neurological conditions do not interfere with brain parts responsible for motor adaptation while others prohibit this function [12]. In this situation, gamification of rehabilitation can provide a sound framework for personalised motor learning while at the same time increasing the enjoyment of therapy.

Wiemeyer et al. [13] pose a critical question: To what extent is virtual game-based perceptual-motor training transferable to real motor tasks? Previous research has shown that training simple tasks in virtual environments not only increases user performance in these environments themselves but in real life tasks as well, indicating a positive transfer of learning [14]. However, real life skills have increased complexity and the improvement of movement quality cannot be described by improvement in simple tasks. In a recent review, Levac et al [15] present the importance of understanding human movement variability in order to develop video games that enhance complex skill learning. They concluded that virtual environments should enable motor learning transfer from therapy to the real world. They state that specific motor skill learning is distinguished from generic motor ability; the former can be improved by specific exergames while the latter depends on several parameters, such as the accuracy of the interface and the fidelity of the virtual tasks. That being said, video games such as the one presented in the current paper are most effective when designed to address specific conditions through targeted sensor and in-game mechanic combinations.

Various motion capture technologies are considered when implementing serious games for rehabilitation. Among the most popular ones are the Nintendo Wii Fit [16], [17] and virtual reality games [18]. Such technologies show great efficacy in this context, as usually they come with plug-and-play hardware and software that are easy to set up in a therapeutic environment. However, they often lack of measurement accuracy; therefore, the sensor-derived data cannot be considered reliable for kinematic analysis at a fine-grained level. Oftentimes, in-game mechanics such as scoring are used for the evaluation of therapeutic outcomes [16], [17]. While in-game score can be an indicator of progress, it is not clear whether the game's score accurately represents the rehabilitational effectiveness of the exergame.

A method that can arguably enhance the robustness and fidelity of said games is "in the wild" data collection (i.e., application in non-laboratory settings). Listman et al. [19] present an analysis of a large longitudinal dataset which was collected in ecologically valid settings for motor learning. They conclude that motor acuity – the ability to execute actions accurately, precisely and in less time – improves faster through games rather than "traditional" lab-based exercises. On a similar note, Ruth et al. [20] observed through a longitudinal field study on kids that a dancing exergame improved their motivation and group cohesion.

B. Markerless Motion Sensors

Looking deeper into serious games that leverage markerless motion sensor technology, most studies found in the literature discuss the reliability of such sensors for kinematic analysis and assessment of therapeutic methods. For example, D'Antonio et al. [7] used a dual webcam setup and the OpenPose software to capture human motion in a markerless fashion; they validated their results by comparing the measurements to an IMU output. Depending on the camera angles, their setup achieved an accuracy offset that varied between $1.6°$ and $14.0°$. These results show that under optimal circumstances, reliable measurements can be retrieved through simple consumer-level equipment; however, optimal circumstances cannot be guaranteed during therapy even in a laboratory setting. Similar conclusions were made in a relevant study that used the Kinect sensor instead of a webcam [21].

In order to address the aforementioned accuracy issues of markerless motion capture sensors, several studies have used multiple devices recording human subjects from multiple angles [22]–[24]. In particular, Rodrigues et al. [23] used a combination of IMU and Kinect sensors; Kinects were used mainly as game avatar controllers, meanwhile Shimmer IMUs were employed to complement the innate inaccuracy of the Kinect. Their setup showed a maximum of 98% similarity to measurements retrieved from Vicon, which is a golden standard in motion capture technology. However, they discuss that several limitations remain unsolved, such as high cost, limited availability, and unsuitability for certain clinical use cases.

Lange et al. [25] touch upon an interesting facet of markerless motion capture-based games by pointing out that players can "cheat" inaccurate trackers by performing a minimal movement instead of the desired one (e.g. twisting their wrists when using a remote controller instead of a full arm swing). To address that possibility, they present the OpenNI software that is based on a supervised calibration session during which the appropriate movements are recorded and used as a baseline to assess the validity of any subsequent move the player makes. In the current study, we follow a similar approach by including short pre- and in-game calibration sessions to ensure that the players' movements are performed and measured appropriately.

C. High-Fidelity Motion Sensors in Games

High-fidelity motion sensing technology is often dismissed because of its high cost or installation and maintenance complexity. However, over the recent years such technology (e.g., accelerometers and gyroscopes) has found its way into everyday devices such as smartphones, which consequently can be employed for clinical purposes [26]. Moreover, the demand for accurate and affordable modern IMU sensors has lead to the production of easy-to-use, off-the-shelf hardware and software solutions. Instrumentation technology also advances rapidly; modern sensors such as variating IMUs can take up a multitude of tasks with different demands, including high accuracy and resolution, low noise and low power consumption. Internet-of-things-related technologies also provide advanced acquisition devices, with "smart" capabilities regarding functionality, communication, storage, portability, and self-validation. Such devices are not limited by lighting conditions (which can be fairly disruptive when using camera-based sensors) and can be used in any location [27].

Chen et al. [28] presented the HP2 posture protector system, a smart suit-based solution to encourage office workers to perform necessary stretching exercises in order to avoid sedentary

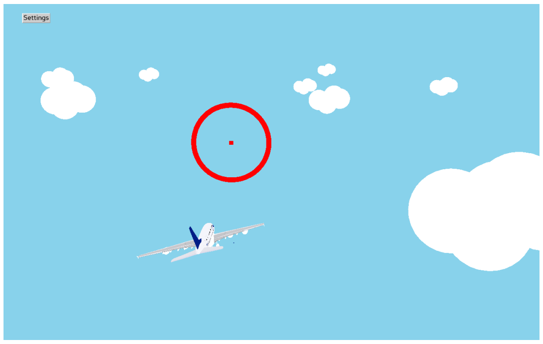

Fig. 1. A screenshot of the FLIGHT video game. The settings of the game (e.g., the airplane's forward velocity) can be changed at the top left of the screen.

work-based pain and improve body posture. However, a smart suit may be considered an intrusive setup as far as daily use is concerned. In similar fashion, Huang et al. [29] employed a data glove platform which provided rich data for kinematic analysis, but also suffered from applicability limitations on a regular basis.

Wittmann et al. [30] proposed a user-friendly setup which uses three IMU sensors: two on the lower and upper arm, and one on the user's trunk. Through that setup, they ran a pilot test with 5 chronic stroke patients who trained at home, without therapist supervision for a period of 6 weeks. Their results show that the patients' in-game assessed 3D workspace grew by 10.7%, while their score on the Fugl-Meyer Upper Extremity scale improved by 5 points on average. They argue that their proposed setup can be viable in an unsupervised, home therapy setting.

III. EXPERIMENTAL SETUP

The framework proposed in this paper is divided in three main components: (a) the video game, (b) a set of external sensors that serve both as game controllers and data collection modalities, and (c) a data processing pipeline, from raw sensor data to game avatar movement translation. An overview of the hardware setup is illustrated in Figure 2.

A. The FLIGHT Game

We have implemented a 3D video game, which revolves around the control of an aircraft in the vertical and horizontal dimensions. The game's goal is flying the aircraft through a series of targets, of which the position in 3-dimensional space can be pre-defined. A snapshot of the game is illustrated in Figure 1. Depending on the computer's processing capacity, this game runs at a frame rate that varies between 22 and 30 frames per second. The game was built using the Panda3D SDK in the Python programming language.

Graphically, we opted for a relatively simple approach since at this stage of this research we wish to put emphasis on the game's fidelity and responsiveness rather than its aesthetics. The background is coloured sky blue and non-collidable clouds are randomly placed below the flight path. The targets' centres are indicated by a small square in order to encourage

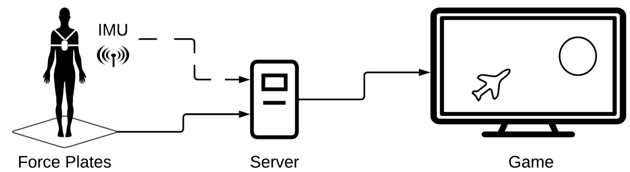

Fig. 2. Overview of the framework's hardware setup. FPs and IMUs are connected to a TCP server via cable and bluetooth respectively. The server processes the raw sensor signals, translates them into game avatar controls and transmits them to the game via another TCP connection.

the player to pass through the target as close to the centre as possible. After the aircraft passes through – or misses – a visible target, that target is hidden and the next one is shown. The z-axis (depth) distance between the targets is pre-defined in the game's settings.

The aircraft's forward velocity is set at a stable value and can only be changed manually through the game's settings. However, both the horizontal and vertical rotation and movement velocity are directly attached to the external sensors' output. In brief, the intensity of motion captured through the sensors is directly related to the displacement rate of the aircraft both horizontally and vertically. Both the aircraft and the targets are bound by minimum and maximum x and y coordinate values, to ensure that the game elements will always stay visible on the screen.

From a therapeutic perspective, the targets can be positioned in such a way that they engage the player to perform a certain movement. For example, a target placed at the top right-most position followed by a target placed at the bottom left-most position requires an intense and rapid response by the player. Even though the current version requires the targets' positions to be defined before the game starts, future versions of the game may also involve real-time generation of targets based on the player's performance in the current or previous sessions or targets.

B. External Sensor Setup

In order to control the aircraft and simultaneously collect high-fidelity data regarding the players' movements, we have opted for 9 degrees of freedom IMUs, strapped onto the player's torso, and two force plates placed below the player's feet (one under each foot). The IMUs incorporate a gyroscope, accelerometer and magnetometer which are sampled at 500 Hz, meanwhile the force plates (with strain gauges) retrieve pressure measurements in two axes (horizontal and vertical) at 200 Hz. The IMUs are custom developed, within the scope of capturing kinematic information during the movement of human subjects [31]. The custom hardware implementation is accompanied by a general-purpose software developed in a .NET environment, focusing on accurate and on-time data retrieval and synchronisation of all incoming signals. A pair of K-Invent [32] Deltas FPs were used to measure ground reaction forces. The force data were recorded in synchronisation with the IMU data using the aforementioned software.

The game is designed to be controlled by one sensor at a time. In the case of IMUs, forward and backward torso rotations steer the aircraft downwards and upwards respectively, while left and right torso rotations steer the aircraft leftwards and rightwards respectively. In the case of force plates, forward or backward displacement of the centre pressure steers the aircraft downwards and upwards respectively, while left or right COP displacement steers the aircraft leftwards or rightwards respectively.

C. Data Processing Pipeline

The sensors' raw data are captured through a proprietary RF (2.4GHz) communication implementation (in the case of IMUs) or a wired serial connection (in the case of FPs). No commercial protocol was selected (e.g., Bluetooth or WiFi) in order to avoid unpredictable delays and provide better control of the power consumption of the devices. The raw data are collected and stored through the .NET custom application and streamed in real-time through a TCP connection to the computer that runs the game. TCP was utilised as the means of communication between programs at the various stages of this framework, and as the means to exchange data between different computers if needed, with no location limitation. A Python TCP server script was built to receive the data and process them as follows:

1) IMUs: The raw signals of gyroscope, accelerometer and magnetometer are used as inputs to a filter fusion algorithm [33]. The algorithm translates these signals into a rotation quaternion in 3 axes. At each timestamp (every 2 milliseconds), a quaternion is computed as the derivative of the current minus the exact previous value of the sensor's orientation in 3-dimensional space. To deal with the cumulative error (drift) in the sensor's measurements, we collect the sensor's static output when resting on a flat surface and subtract the average error value from every measurement for all axes.

At the start of the game we used the acceleration vector to extract a baseline when the participant is stable and in an upright stance; we call this recording the measurement of verticality. During game play, whenever the user is found to be "vertical" for more than 0.2 seconds, we reset the baseline rotation quaternion according to the vertical position. Finally, the quaternion is transformed into yaw pitch and roll angles following [33]. The quaternion extraction process is ordinal, thus it requires the complete set of the acquired IMU data at 500 Hz. However, TCP communication is prone to random delays, therefore in order to reliably transmit and accurately process the acquired data, a custom (batch) communication protocol was implemented. The extraction of quaternions and transformation to yaw, pitch and roll angles were applied to to raw data (at 500 Hz). The angular data were downsampled to 25 Hz and transmitted to the game through a second TCP connection.

2) Force plates: Regarding FP data, the COP is calculated in real time and compared to a baseline (vertical) position of the user in order to compute the direction of the displacement.

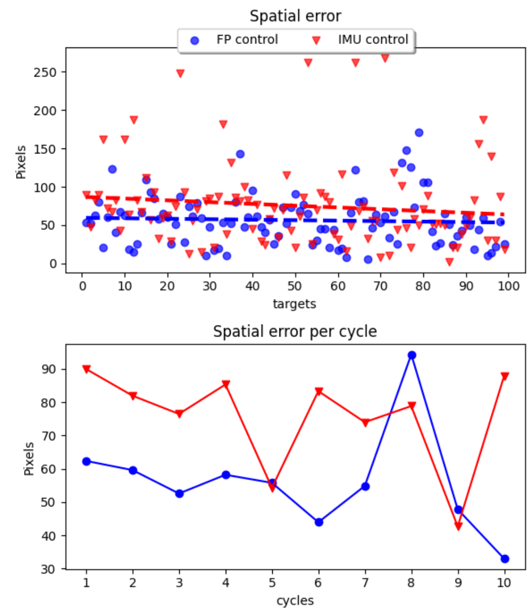

Fig. 3. Spatial error in pixels, per target (top) and per 10 target cycle (bottom). Dashed lines in the top figure represent the linear regression line for the two sessions under FP (bottom dashed line) and IMU (top dashed line) control. Error is measured as the euclidean distance between the aircraft and the centre of each target at the moment of achievement or non achievement of that target.

The FP signals are highly reliable and straightforward and therefore require minimal pre-processing.

After pre-processing, the curated FP signals are downsampled to 25Hz and transmitted at that frequency through the second TCP connection from the server to the game software. COP values do not rely on previous samples, therefore the downsampled data was transmitted instead of the complete set of the acquired data (at 500Hz). We opted for the bulk of the signal processing to be implemented on the TCP server in order to minimise the number of computations performed by the game itself, therefore maximising its frame rate.

IV. Pilot Study

In this part we present results obtained from a single human subject playing both under FP (first session) and IMU (second session) controls for 100 targets each. Both sensors were attached to the subject in both sessions. The subject was aware of which sensor was the assigned game controller in each session. The subject is a 23 year old healthy female with little experience in video game play and no experience in motion-controlled video games in particular. This pilot study was her first ever interaction with this game. Before game play, each controller sensor was calibrated by instructing the subject to perform the maximum possible motion in both directions of the X and Y axes. This resulted in the calculation of a baseline that was used to normalise sensor measurements during game play, based on the maximum range of motion of that specific user.

Apart from only measuring the raw number of achieved targets (targets the player successfully went through), we

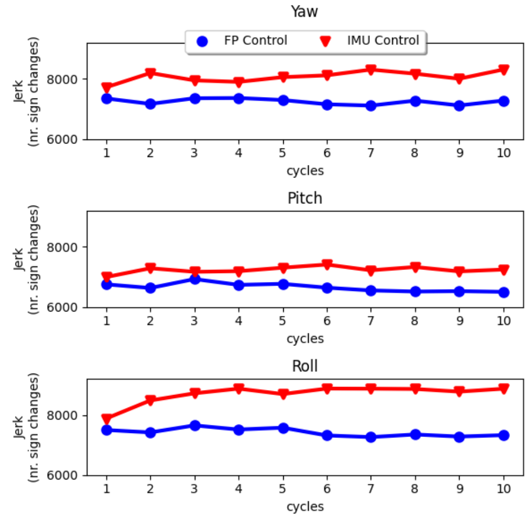

Fig. 4. Angular jerk (smoothness) for each rotational axis. In blue colour (circle marker) and red colour (triangle marker) we indicate the sessions in which the FP and the IMU were used as the game's controller respectively.

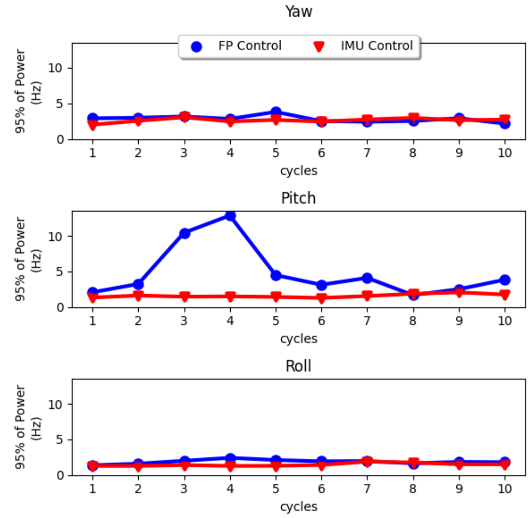

Fig. 5. Power spectrum of angular velocity of the IMU sensor per rotational axis. In blue colour (circle marker) and red colour (triangle marker) we indicate the sessions in which the FP and the IMU were used as the game's controller respectively.

also calculated spatial error. The spatial error is computed for each target separately and represented by the euclidean distance between the aircraft and the centre of the target at the moment of achievement or non achievement of the target (see Figure 3b). Spatial error results are averaged every ten targets resulting in ten cycles of ten targets each. Each target has a radius of 50 pixels, thus a spatial error measure above 50 pixels represents a missed target (see Figure 3a).

Motor learning however, is not quantified by in-game measures only. The smoothness and the power spectrum of movement are variables that resemble learning [34], [35]. The smoothness of the movement is quantified by calculating the jerk (the second derivative of the angular velocity) and, specifically, by counting how many times the jerk signal changes sign (from positive to negative and vice-versa). Results of these analyses are presented in Figure 4 for each movement axis and for each control separately.

Motor learning is also encapsulated in the frequency of the rotational movement of the torso. The frequency can be quantified by calculating the power spectrum of the movement signal and detecting the frequency which corresponds to at least 95% of the signal. These frequencies are calculated per 10 target cycle, for each rotational axis separately when analysing angular velocity (Figure 5) and ground plane axis when analysing the COP (Figure 6).

V. Discussion

This paper presents a complete framework for gamified motor learning through a serious game, high-fidelity motion sensors and a motion signal analysis pipeline for game avatar control and post-game user performance analysis. We employed this framework in a medical laboratory, where a human subject played two brief sessions while IMU and FP sensor signals were used as controllers in each session respectively.

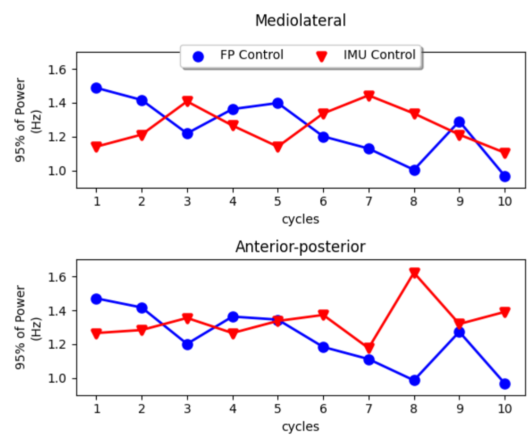

Fig. 6. Power spectrum of COP (FP sensor) per ground plane axis. In blue colour (circle marker) and red colour (triangle marker) we indicate the sessions in which the FP and the IMU were used as the game's controller respectively. The third axis (vertical to the ground) is omitted as it is not relevant for the FP sensor.

We illustrate relevant methods for post-hoc performance assessment which are based both on in-game metrics as well as fine-grained motion signal analysis.

As far as game data are considered, a trivial method of measuring user performance is through the game score, which is represented by the raw number of achieved targets. To that we add a supplementary metric, namely the spatial error. The human subject was instructed to try to pass through the target, and as close to the centre of each target as possible, therefore the latter metric allows us to examine in-game performance in more detail. In particular, it enables us to discriminate between users that perform at the minimum required level (just enough movement to pass through a target) and users that put in the effort required to pass through the centre of each single target. In the current case, despite the relative spatial error reduction, the player performed better overall under FP control (first session).

As far as sensor data are considered, in Figures 4 – 6 we present a wide span of motion signal analyses which are not only capable of assessing the range and quality of the motor skills of the user but also the rate of the user's motor learning. In particular, looking at the top of Figure 4 we observe that the user maintained an overall consistent amount of jerk (smoothness) in the rotational movement of their torso. Decrease in this metric has been proven to be correlated to positive motor learning, i.e., performing a repetitive motor skill successfully through time. Although there is no downward trend in neither of the sessions, we can observe that jerk was higher for the session under IMU control. This indicates that the torso had smoother rotational movement under FP control, which means that the subject was able to distinguish between the two controls and use different motor patterns for each. When playing under FP control, the subject managed to maintain a smooth torso movement despite the necessary weight-shifting. Moreover, the user showed relative improvement in in-game performance (see Figure 3) as the spatial error tends to decrease over time.

Figures 5 and 6 illustrate a power spectrum analysis of the torso's angular velocity and COP under both controls (IMU and FP) respectively. The power spectrum analysis indicates fluctuations in the frequency of the player's movements per cycle (10 targets). The power spectrum is imprinted in the frequency under which the 95% of the signal is present. Looking at the bottom of Figure 5, we can observe a consistently low frequency in roll (rotation around the vertical axis), which is a redundant movement for both control conditions (it does not affect the aircraft's movement). However, in Figure 5b we can clearly see an increase in pitch (leaning forwards or backwards) frequency between targets 20 and 50. This could be translated as the player's attempt to control the aircraft with faster and more frequent movements until realising that high-frequency movements are not efficient, hence the drop in frequency in targets 50 to 100.

The high variation in pitch velocity seems to occur only under FP control. This can be explained by the nature of this particular sensor. Under FP control, the subject must displace their COP in order to move the aircraft. It is a fact that a vast number of bodily movements can ultimately be translated into COP displacement. On the contrary, trunk rotations (measured by IMUs) contain less inherent variety. This multitude of motor "solutions" that is imposed by the different controls results in the torso's frequency fluctuations under the FP control session. There, the subject seems to change their motor patterns in order to explore more efficient game play solutions. This is less possible under the more strict and task-specific IMU control.

The frequency fluctuations of the COP displacement in the two axes of the ground plane during both sessions are shown in Figure 6. There, we observe more frequency fluctuations compared to the IMU sensor (Figure 5) as well as a consistent decrease in fluctuation under FP control (Figures 6a and 6b). The latter may be explained by the high-fidelity visual feedback (aircraft movement) deriving from COP displacement. In particular, a decrease in COP displacement fluctuations would immediately translate to a decrease in the aircraft's movement frequency on the screen. The COP fluctuation decrease in Figure 6 can be an indication of motor learning as the subject managed to reduce frequency of movement while maintaining a consistent in-game performance (consistent spatial error – see Figure 3a).

In order to reach concrete conclusions about the efficacy of the present framework, longitudinal data from a diverse set of users needs to be collected. Through the conducted pilot study we were able to extract reliable, high-frequency metrics of motor performance. Our pilot user reported that the game was easy to familiarise with and the goals of the gamification framework were clear. However, the current setup cannot easily be transferred to the home environment, as far as the complexity, cost and connectivity of the software and hardware components are concerned. Therefore, one of the main points for future improvement of the system is the incorporation of wireless and cost-effective sensors that will enable plug-and-play installation as well as remote monitoring of patient rehabilitation from the therapist. Furthermore, a minimum level of familiarity with sensor self-placement and computer software is required, which may pose a limitation on particular user groups (e.g., elderly population).

Moreover, we believe that the current setup enables generalisation (i.e., transferability) of this framework to a wide variety of serious games. Since sensor signal pre- and post-processing is performed in an intermediary server, the exact same data could be used both for in-game avatar control and post-game analysis regardless of the game used, as long as the user's movements are mapped to similar in-game mechanics. Ultimately, our aim is to employ this framework in order to generate personalised game sessions for motor learning based on predictive user modelling.

VI. Conclusion

In this paper, we have discussed the implementation of a serious game which enables motor learning sessions through the use of high-fidelity external motion sensors. The current framework was used in a pilot study through which we illustrated methods for user motor performance analysis based both on in-game and sensor data. This setup will be used in longitudinal user studies with the goal of providing a platform for personalised games for motor learning.

References

[1] J. Janssen, O. Verschuren, W. J. Renger, J. Ermers, M. Ketelaar, and R. Van Ee, "Gamification in physical therapy: More than using games," *Pediatric Physical Therapy*, vol. 29, no. 1, pp. 95–99, 2017.

[2] G. Amprimo, G. Masi, C. Ferraris, G. Olmo, and L. Priano, "A preliminary comparison between traditional and gamified leg agility assessment in parkinsonian subjects," in *2022 IEEE 10th International Conference on Serious Games and Applications for Health(SeGAH)*, 2022, pp. 1–8.

[3] J. M. Paavola, K. E. Oliver, and K. I. Ustinova, "Use of x-box kinect gaming console for rehabilitation of an individual with traumatic brain injury: A case report," *Journal of Novel Physiotherapies*, vol. 3, no. 01, pp. 1–6, 2013.

[4] K. McNamara, A. P. L. Bo, A. McKittrick, G. Tornatore, S. Laracy, and M. Desselle, "Markerless motion capture system to detect upper limb movement during rehabilitation using video games," in *2022 IEEE 10th International Conference on Serious Games and Applications for Health(SeGAH)*, 2022, pp. 1–6.

[5] P. Jonna and M. Rao, "Design of a 6-dof cost-effective differential-drive based robotic system for upper-limb stroke rehabilitation," in *2022 44th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*. IEEE, 2022, pp. 1423–1427.

[6] W. K. Koh, Q. H. Nguyen, Y. O. Yang, T. Xu, B. P. Nguyen, and M. C. H. Chua, *End-to-End Hand Rehabilitation System with Single-Shot Gesture Classification for Stroke Patients*. Cham: Springer International Publishing, 2021, pp. 59–67. [Online]. Available: https://doi.org/10.1007/978-3-030-76620-7_5

[7] E. D'Antonio, J. Taborri, I. Mileti, S. Rossi, and F. Patané, "Validation of a 3d markerless system for gait analysis based on openpose and two rgb webcams," *IEEE Sensors Journal*, vol. 21, no. 15, pp. 17 064–17 075, 2021.

[8] E. D'Antonio, J. Taborri, E. Palermo, S. Rossi, and F. Patane, "A markerless system for gait analysis based on openpose library," in *2020 IEEE International Instrumentation and Measurement Technology Conference (I2MTC)*. IEEE, 2020, pp. 1–6.

[9] N. Nakano, T. Sakura, K. Ueda, L. Omura, A. Kimura, Y. Iino, S. Fukashiro, and S. Yoshioka, "Evaluation of 3d markerless motion capture accuracy using openpose with multiple video cameras," *Frontiers in sports and active living*, vol. 2, p. 50, 2020.

[10] A. L. Betker, T. Szturm, Z. K. Moussavi, and C. Nett, "Video game–based exercises for balance rehabilitation: A single-subject design," *Archives of Physical Medicine and Rehabilitation*, vol. 87, no. 8, pp. 1141–1149, 2006. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S000399930600356X

[11] I. Cikajlo, M. Rudolf, R. Mainetti, and N. A. Borghese, "Multi-exergames to set targets and supplement the intensified conventional balance training in patients with stroke: A randomized pilot trial," *Frontiers in Psychology*, vol. 11, 2020. [Online]. Available: https://www.frontiersin.org/articles/10.3389/fpsyg.2020.00572

[12] T. Kitago and J. W. Krakauer, "Chapter 8 - motor learning principles for neurorehabilitation," vol. 110, pp. 93–103, 2013. [Online]. Available: https://www.sciencedirect.com/science/article/pii/B9780444529015000083

[13] J. Wiemeyer and S. Hardy, "Serious games and motor learning: concepts, evidence, technology," in *Serious games and virtual worlds in education, professional development, and healthcare*. IGI Global, 2013, pp. 197–220.

[14] V. Hatzitaki, D. Voudouris, T. Nikodelis, and I. Amiridis, "Visual feedback training improves postural adjustments associated with moving obstacle avoidance in elderly women," *Gait & Posture*, vol. 29, no. 2, pp. 296–299, 2009. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0966636208002932

[15] D. Levac, M. Huber, and D. Sternad, "Learning and transfer of complex motor skills in virtual reality: a perspective review," *Journal of NeuroEngineering and Rehabilitation*, vol. 16, no. 1, pp. 121–136, 2019. [Online]. Available: https://jneuroengrehab.biomedcentral.com/articles/10.1186/s12984-019-0587-8

[16] F. A. dos Santos Mendes, J. E. Pompeu, A. M. Lobo, K. G. da Silva, T. de Paula Oliveira, A. P. Zomignani, and M. E. P. Piemonte, "Motor learning, retention and transfer after virtual-reality-based training in parkinson's disease – effect of motor and cognitive demands of games: a longitudinal, controlled clinical study," *Physiotherapy*, vol. 98, no. 3, pp. 217–223, 2012, special Issue on Advancing Technology including papers from WCPT. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S003194061200051X

[17] B. C. Smits-Engelsman, L. D. Jelsma, G. D. Ferguson, and R. H. Geuze, "Motor learning: an analysis of 100 trials of a ski slalom game in children with and without developmental coordination disorder," *PloS one*, vol. 10, no. 10, p. e0140470, 2015.

[18] M. Demers, K. Fung, S. K. Subramanian, M. Lemay, and M. T. Robert, "Integration of motor learning principles into virtual reality interventions for individuals with cerebral palsy: Systematic review," *JMIR Serious Games*, vol. 9, no. 2, p. e23822, Apr 2021. [Online]. Available: https://games.jmir.org/2021/2/e23822

[19] J. B. Listman, J. S. Tsay, H. E. Kim, W. E. Mackey, and D. J. Heeger, "Long-term motor learning in the "wild" with high volume video game data," *Frontiers in human neuroscience*, vol. 15, p. 777779, 2021.

[20] M. Rüth and K. Kaspar, "Exergames in formal school teaching: A pre-post longitudinal field study on the effects of a dance game on motor learning, physical enjoyment, and learning motivation," *Entertainment Computing*, vol. 35, p. 100372, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S187595212030080X

[21] C.-Y. Chang, B. Lange, M. Zhang, S. Koenig, P. Requejo, N. Somboon, A. A. Sawchuk, and A. A. Rizzo, "Towards pervasive physical rehabilitation using microsoft kinect," in *2012 6th international conference on pervasive computing technologies for healthcare (PervasiveHealth) and workshops*. IEEE, 2012, pp. 159–162.

[22] S.-h. Lee, D.-W. Lee, K. Jun, W. Lee, and M. S. Kim, "Markerless 3d skeleton tracking algorithm by merging multiple inaccurate skeleton data from multiple rgb-d sensors," *Sensors*, vol. 22, no. 9, p. 3155, 2022.

[23] T. B. Rodrigues, C. Ó. Catháin, D. Devine, K. Moran, N. E. O'Connor, and N. Murray, "An evaluation of a 3d multimodal marker-less motion analysis system," in *Proceedings of the 10th ACM multimedia systems Conference*, 2019, pp. 213–221.

[24] Y.-C. Du, C.-B. Shih, S.-C. Fan, H.-T. Lin, and P.-J. Chen, "An imu-compensated skeletal tracking system using kinect for the upper limb," *Microsystem Technologies*, vol. 24, pp. 4317–4327, 2018.

[25] B. Lange, C.-Y. Chang, E. Suma, B. Newman, A. S. Rizzo, and M. Bolas, "Development and evaluation of low cost game-based balance rehabilitation tool using the microsoft kinect sensor," in *2011 annual international conference of the IEEE engineering in medicine and biology society*. IEEE, 2011, pp. 1831–1834.

[26] F. Gu, C. Xia, and Y. Sugiura, "Augmenting the boxing game with smartphone imu-based classification system on waist," in *2022 International Conference on Cyberworlds (CW)*. IEEE, 2022, pp. 165–166.

[27] Z.-X. Yin and H.-M. Xu, "A wearable rehabilitation game controller using imu sensor," in *2018 IEEE international conference on applied system invention (ICASI)*. IEEE, 2018, pp. 1060–1062.

[28] H.-Y. Chen, T.-Y. Lin, L.-Y. Huang, A.-C. Chen, Y.-C. Zheng, H.-M. Wang, S.-Y. Wei, and Y.-Y. Chou, "Hp2: using machine learning model to play serious game with imu smart suit," in *Proceedings of the 17th International Conference on Mobile and Ubiquitous Multimedia*, 2018, pp. 397–402.

[29] M.-C. Huang, E. Chen, W. Xu, and M. Sarrafzadeh, "Gaming for upper extremities rehabilitation," in *Proceedings of the 2nd Conference on Wireless Health*, 2011, pp. 1–2.

[30] F. Wittmann, O. Lambercy, R. R. Gonzenbach, M. A. van Raai, R. Höver, J. Held, M. L. Starkey, A. Curt, A. Luft, and R. Gassert, "Assessment-driven arm therapy at home using an imu-based virtual reality system," in *2015 IEEE international conference on rehabilitation robotics (ICORR)*. IEEE, 2015, pp. 707–712.

[31] V. Konstantakos, T. Nikodelis, I. Kollias, and T. Laopoulos, "Automated measurement system based on digital intertial sensors for the study of human body movement," in *Proceedings of the 6th IEEE International Conference on Intelligent Data Acquisition and Advanced Computing Systems*, vol. 1, 2011, pp. 76–80.

[32] "Kinvent inc, montpellier, france," [Online] Available: https://physio.kinvent.com/.

[33] S. Madgwick, A. Harrison, and R. Vaidyanathan, "Estimation of imu and marg orientation using a gradient descent algorithm," pp. 1–7, 2011.

[34] C. Bloomer, S. Wang, and K. Kontson, "Kinematic analysis of motor learning in upper limb body-powered bypass prosthesis training," *PLOS ONE*, vol. 15, pp. 1–16, 01 2020. [Online]. Available: https://doi.org/10.1371/journal.pone.0226563

[35] M. Kojima, S. Obuchi, K. Mizuno, O. Henmi, and N. Ikeda, *Journal of physiological anthropology*, vol. 27, no. 4, pp. 193–200, 2008.