Characterization of Upper Limb Functionality Caused by Neuromuscular Disorders using Novel Motion Features from a Specialized Gaming Platform

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Abstract: This paper describes the methodology for analyzing upper limb motion data derived from a novel Gamified Motion Control Assessment platform that is based on a virtual 3D game environment. The gamified approach targets patients experiencing upper-limb movement hindrances, typically caused by neuromuscular disorders. The leap motion controller is used for interaction. The game guides the avatar to move along the X and Y axis following specific paths. The avatar mimics the movement of the user's hand that performs these movements for rehabilitation. In order to use this method for the training and assessment patient's motion, a quantified approach that uses the game-based motion for patient assessment is required. Besides simple game scores that are often used, the proposed data analysis aims to elaborate on the discrimination between pathological and healthy movement with a machine learning approach, as well as the quantification of the patient's progress over time. For this purpose, movement and performance-related features were extracted from the leap sensor recordings and their value was explored towards characterizing the patient state and progress in detail. A dataset with multiple recordings from patients and healthy individuals was used for this purpose. All patients suffered from neuromuscular disorders. The features with the highest discriminatory value between the two groups were subsequently used to develop a set of classifiers for different sets of movements (e.g., horizontal, diagonal, vertical). A patient was left out of the classifier creation procedure and used for external validation. The models achieved high accuracy (92.13%). These results are deemed promising for the quantification of a patient's progress.

1 INTRODUCTION

Motor control is a complex process or a set of sub-processes that involves the coordination of muscles and limbs in order to perform a motor skill either voluntary or as a reflex. Humans from birth are trained in motor control by integrating sensory-motor information, a procedure called Motor-learning. Firstly, through observation and later via repetition, movements are consolidated in the Central Nervous System (CNS). Certain pathologies or injuries affect the CNS resulting in the loss of cognitive functions of the brain. This may impact several motor functions and cause partial or complete loss.

Rehabilitation programs aim to detect motor deficits and help patients regain control of their movements through motor learning. The standard procedure is the repetitive training of isolated movements' correct form.

There has been an increasing amount of studies regarding the assistance of physical rehabilitation and conventional treatment methods via technology

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(Meijer et al., 2018),(Ang and Guan, 2013). This interest in technology-based rehabilitation has led to the development of an emerging domain that combines exergames, gamification mechanisms and traditional rehabilitation methodologies (Smeddinck et al., 2015). These novel treatment methodologies combine software and hardware to facilitate the process of Motor Learning, by introducing an efficient (Veerbeek et al., 2017) and more rewarding way of performing a series of repetitive and functional movements, which are required for the rehabilitation of patients with motor deficits.

Gamification and serious gaming are regarded as means for inducing positive health behavioural change (Sardi et al., 2017), but there is still lack of solid evidence and consolidated approaches and means for quantification progress.

There are various research approaches that are integrating Leap motion sensor in their system. One example is a system that was suggested in 2014 (Charles et al., 2014) for the rehabilitation of wrist and fingers that used Leap as a part of a game that engaged the user to pick up various objects and place them correctly in order to form a specific shape or construction. Another example is a system (Elnaggar and Reichardt, 2017) that was also suggested for the rehabilitation of hand, wrist and fingers and was trying to exercise hand's grip and movement.

Overall, gamification mechanisms integrated appropriately in standard therapy regimens and protocols, have been found to be sufficiently effective in a wide range of diseases involving motion, for example in stroke (Henderson et al., 2007; Tamayo-Serrano et al., 2018) or in Parkinson's disease with leap motion (Oña et al., 2018).

The current work is based on a custom rehabilitation platform that can be used as a tool for the medical treatment of patients with physical impairments of the upper limbs (Chytas et al., 2020), including arm, axilla and shoulder. It supports the idea of a 'gaming as a health service' (GaaHS), providing the physician the ability to remotelly monitor patients and adjust their treatmeant. The platform is aiming to optimize the Motor Control and Learning processes by providing an engaging way for rehabilitation exercise execution along with a set of statistical tools that evaluate quantitatively the patient's upper limb motion and overall performance.

The analysis of upper limb motion is a challenging task due to its multidimensional nature. We propose a novel set of features that characterizes upper limb motion along with gameplay related features. Our aim is to establish a baseline that can distinguish between healthy and pathological movement and additionally quantify the patient's rehabilitaion progress and improvement.

2 BACKGROUND AND RATIONALE

Currently, the GaaHS platform (Chytas et al., 2020) consists of one game scenario that incorporates basic rehabilitation exercises in its mechanics. It follows the flying simulation paradigm. The user is asked to guide a red polygon airplane (avatar) through orthogonal game objects (gates) that are placed across the scene. The interaction between the user and his avatar is achieved by the camera sensor Leap Motion Controller, which utilizes computer vision technology to recognize hands in its field of view and calculates a set of measurements that describe them. The general therapy protocol focuses on these exercise movements: horizontal adduction/abduction of the shoulder, and supination/pronation of the forearm. The hand is placed above the sensor and moves along the horizontal and vertical plane, as well as rotate along the Z-axis. In the virtual world of the game, the airplane mimics the hand's movement. Because of the strictly defined set of movement exercises, it was a requirement-based design decision that the airplane avatar of the game cannot move with six degrees of freedom. Thus, the airplane's movement is confined to the X and Y plane, a restriction that made it quite challenging to achieve a degree of immersion of the user in the game world. The gate objects that the user leads the aircraft through, appears in a predefined 3x3 grid Figure 2. The goal is the highest possible number of repetitions, so the condition for the end of a game session is either a time limit or a limit on the number of the gates. A secondary objective of the game is to collect the 'coins' that are placed in the middle of a gate. This provides the user with a clear target of where he/she should aim to "fly" through, and it might later be helpful in discerning patterns during the analysis process.

After the completion of the course, a score is awarded to the user that represents the number of gates he/she managed to go through. A rough metric of the performance is the percentage of successful gates. This score is useful both as a means for motivating the user and as a summarized, high level index of the user's ability to perform the task, useful for the rehabilitation healthcare professional. However, it is questionable whether this index is adequately informative for the patient's detailed condition or for specific problems in movement and their progress over time.

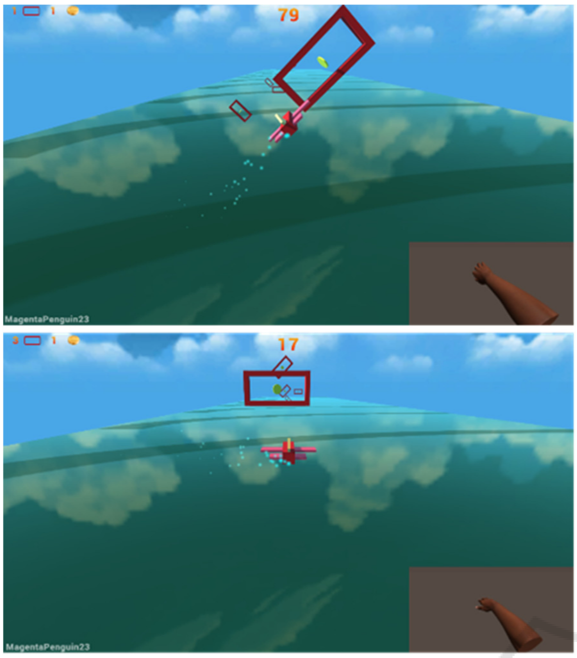

Figure 1: Movement of the hand and its effect on the virtual world of the game.

Similar studies use the respective game score and task completion time features to evaluate the patient's progress (De Leon et al., 2014) while others delve further into analysing the trajectory using motion features (Tang et al., 2017). We propose a new strategy that enables detailed evaluation combining elements of both approaches. We split hand movement into discrete segments resulting in more detailed time characteristics, use derived trajectory characteristics (such as acceleration per axis), we also include a variation of our game score (proximity to the target instead of success or failure) and distinguish between groups of movement that are activated by different muscle groups. Our approach is based on fine grained time features with a combination of commonly used motion characteristics that derive from medical needs and are meaningful to the physician.

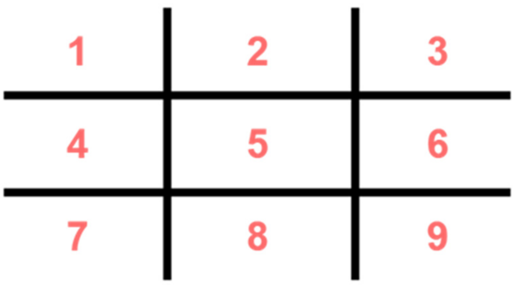

Figure 2: Gates 3x3 grid where the gates appear.

3 MATERIAL AND METHODS

The main focus of the analysis on the current stage is to determine the variables that are going to be examined and explore the differences between healthy and pathological movement.

Our hypothesis is that the proposed movement features differ among healthy subjects and patients, and that they reflect changes over time. Regarding the classification of movement, a two-phase procedure was followed. In Phase 1, we examined if the creation of such classifiers is feasible using a dataset consisting of healthy subjects and patients. In Phase 2, we used external data to verify the results.

3.1 Data

For this analysis, we collected data from 8 subjects; 3 patients undergoing rehabilitation and 5 healthy individuals not diagnosed with a related motor control / central neural system disorder. Healthy subjects were of ages 25-38 with one of them being female (20%), while all patients are males in their 20s. The patients performed the games using the hand in need of physiotherapy (right hand in both cases) while the healthy subjects were using their dominant hand (20% were left-handed). Those gaming sessions were in addition to the routinely prescribed physiotherapy treatment the patients were receiving at that time. The data acquisition protocol was approved by the Bio-ethics committee at the Aristotle University of Thessaloniki (AUTH) and the patients signed a consent form.

The data acquisition for the healthy subjects lasted 2 weeks, while the patients' data were retrieved based on the amount of time they were receiving physiotherapy, the occurrence rate of the therapy, and the settings the physician deemed proper based on their current condition and general progress. An upcoming pilot will follow a more refined protocol for all participants. The healthy subjects performed 2 sessions per week for 2 weeks (4 sessions total). The first week's sessions were performed in *normal* difficulty settings while the second week's, in *hard* difficulty settings. Each session consisted of 10 games and each game had a duration of 90 seconds. The difficulty settings affect the avatar's constant movement rate on the Z-axis, substantially reducing the time required for the avatar to move from one gate to another. Of note, according to all healthy subjects' feedback, the *normal* settings were more bothersome than the *hard* ones since the subjects were supposed to keep their hand steady for a longer period. Each healthy subject (H1-5) had 4 gaming sessions, 40 games and 800 gates. Percentages of gates the subjects H1-5 successfully navigated through were 1, 0.942, 0.985, 0.995 and 1 respectively.

As far as the patients are concerned, their data have been collected in a span of 9 months (P1) and 6 months (P2 and P3) accordingly. Specifically, P1 had 39 gaming sessions, 652 games played, and went through 19033 gates, P2 had 24 gaming sessions, 378 games and 10300 gates, while P3 corresponding statistics are 16 gaming sessions 184 games and 2107 gates. The difficulty settings were gradually changed from *normal* to *hard* to eventually *very hard* in the span of their treatment for P1 and P2. P3 difficulty settings remained to *normal*. Percentages of successful gates for the patients P1-3 were 0.946, 0.969 and 0.718 respectively.

The dataset used for the classification stage consisted of 4000 gates for the healthy subjects H1-5 and 29333 gates for patients P1,2. The gates were grouped based on the type of movement, vertical, horizontal, diagonal and the direction (e.g., top to bottom, etc.). P3 was used as an external validation dataset.

The distinction of direction was deemed important from a medical viewpoint, since such movements involve the activation of different muscle groups, e.g., horizontal abduction (Latissimus dorsi and posterior fibers of deltoid) and adduction (Pectoralis major and anterior fibers of deltoid) (Elzanie and Varacallo, 2018). This distinction also makes sense from a statistical analysis point of view (e.g., the metrics of the X-axis are expected to differ when the subject performs a horizontal movement vs a vertical one).

3.2 Feature Extraction

The raw data points acquisition rate is tied to the frame rate at which the game runs. Although the frame rate for the game was capped at 60 fps it can occasionally drop below 60, an occurrence more common in systems with low computational capabilities.

Another issue was the artefacts that occurred when the leap sensor failed momentarily to correctly identify the subject's hand, typically other objects interrupting the sensor's field of view or nearby light sources causing interferences. The abrupt changes in the hand trajectory were identified using a high pass filter, followed by an evaluation of the neighbouring area in order to determine which part of the movement was the artefact (if any). The data points that were deemed as artefacts were subsequently removed. Firstly by removing time windows that had more than 25% out of the expected samples missing and afterwards during the analysis.

As a next step, and in order to address both the above issues and to facilitate an analysis that supports exploration in the frequency domain, the time-series of the hand coordinates were interpolated at a steady rate of equivalent to 60 fps.

The gameplay can be distinguished into parts. Each part corresponds to the period between two consecutive gates (time window W_i). The gates (G_i) are moving towards the avatar at a controlled pace. Therefore, all the time windows have the same duration, with the exception of the first gate, which appears a few moments after the start, to provide the user ample time to get accustomed to the game.

Each time window (W_i) is further distinguished into 3 different sub-periods (Figure 3). Those periods were detected by examining the velocity on X and Y-axes, considering the direction and the proximity to the target gate.

1. Response (DT1: t0-t1): it refers to the time period starting when the user has reached the Gi gate until they become aware of the upcoming gate Gi+1, and they begin to move towards it. This is characterized as a Steady state (orange).
2. Movement (DT2: t1-t2): it refers to the time period where the user is moving from Gi towards the upcoming gate Gi+1. This is a Movement state (green).
3. Stabilization (DT3: t2-t3): it refers to the time period from the time point that the user has arrived to the X, Y coordinates that correspond to the Gi+1 gate and is waiting to reach it (plane pass through the gate) until the time the avatar crosses the gate. This is a Steady state (red).

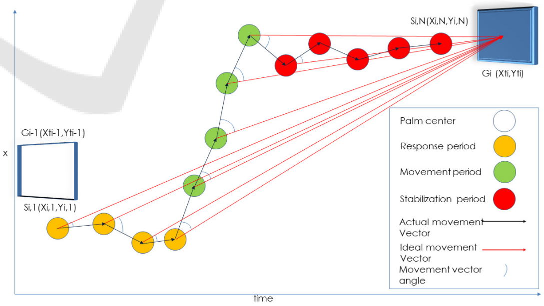

Figure 3: Movement from gate Gi-1 to Gi . The Si,j represents the hand position on each j frame for every i window (Wi).

The features currently examined involve the description of the movement in the time domain (velocity, acceleration, trajectory, jitter, etc.) The distance and the metrics that derive from it (velocity and acceleration) are measured in in-game units.

- Durations of DT1/DT2/DT3 in milliseconds
- Mean/SD Velocity DT1/DT2/DT3 X/Y/both: Mean/Standard deviation of the hand velocity on parts DT1/DT2/DT3 on axis X/Y/ both of them.
- Mean Velocity DT2 start calculated during the first 0.25 seconds of the DT2 part.
- Mean/SD Acceleration DT1/DT2/DT3 X/Y/both: Mean/Standard deviation of the hand acceleration on parts DT1/DT2/DT3 on axis X/Y/ both axes.
- Distances total travelled per time window and total, ratio of minimum movement required to actual
- Total Distance/ Total Distance DT1/DT2/DT3: actual distance travelled during the whole Wi, on parts DT1/DT2/DT3, respectively.
- Minimum distance (final): minimum distance from the center of the gate during the whole Wi movement/ during the final 0.5 sec of the Wi movement

This amounted to a total of 28 features that were subsequently examined.

3.3 Analysis

The gates were grouped based on the type of movement, vertical, horizontal, diagonal and direction. Right to Left (r2l) Left to Right (l2r) , Up to Bottom (u2d), Bottom to Up (d2u) Top Left to Bottom Right (dg1) Top Right to Bottom Left (dg2), Bottom Left to Top Right (dg3), Bottom Right to Top Left (dg4).

The analysis was focused on the subject's performance during the traversal from one gate to another. For each subject, all the calculated movement features were grouped together without the distinction of individual games or sessions. The order in which each gate was traversed was kept intact and as such, we were able to examine the subject's progress through time. In more detail, the analysis consists of following steps:

1. In each cross-validation round, split the dataset into two parts: a) Train: 1 patient (19033 or 10300 gates), 4 healthy subjects (3200 gates), b) Test: 1 patient (19033 or 10300 gates), 1 healthy subject (800 gates)
2. Use one direction at a time (this reduces the number of gates used for the training and testing, e.g. out of the 19033 gates P1 has, 2203 belong in the u2d category)
3. On the training dataset, for each feature, detect values that are outside the range of four times the standard deviation. A single out of bounds value would cause that gate to be excluded. This further addresses the artefact problem during data acquisition.
4. Test the features for normality using the Shapiro–Wilk test (Shapiro and Wilk, 2015) for normality.
5. If the variables were normally distributed, the analysis of variation (AOV) was used, otherwise the Kruskal–Wallis H test was preferred (Kruskal and Wallis, 1952).
6. Adjust the p-values that derived from the above tests using the Bonferroni correction (B. Alt, 2006).
7. Select the statistically significant ($p<0.05$) features.
8. Check those features for correlation using the Pearson formula (Chen and Popovich, 2011).
9. Features that had a high degree of correlation (0.8) were further examined and the worst performing features were removed.
10. Utilize the training dataset with the remaining features and train a neural network model (Kalchbrenner et al., 2014) (these models yielded the best results in the type of data that were used) using an internal k-fold cross-validation with one hidden layer and an adjustable size (range 3 to 15).

The model that was created using data from 5 subjects (4 healthy 1 patient) was tested using the remaining two subjects (1 healthy, 1 patient). The Leave-One-out (a healthy subject and a patient) cross-validation approach was preferred over the k-fold cross-validation with train and test samples mixed from all using those 7 subjects, as this method is less biased, i.e., the hypothesis that patients and healthy subjects differ in their movement patterns can be examined without any bias that is inserted by utilizing the same subjects for testing and training.

After testing the validity of our hypothesis that the movement patterns differ among healthy subjects and that pathological patterns can be identified using classifiers, we created a final set of 8 models, one for each direction. These models were trained with the dataset initially used in Phase 1 as a whole (P1,P2 and H1-5). These classifiers were afterwards used in Phase 2 on P3's data as external validation.

To observe the patients' progress during their treatment, the data points of each feature were aligned in chronological order. Following, they were filtered using a simple moving average window as a low-pass filter to present the underlying trend.

Table 1: The details of the best performing models. Balanced Acc stands for balanced accuracy, Sense for sensitivity, Spec for specificity, Mov. for Movement.

Mov. type	Test Data	Balanced Acc	Sense	Spec	Truth Table	
					2157	2
u2d	P1 – H4	0.979	0.979	0.979	46	96
					1016	1
dgl	P1 – H4	0.978	0.980	0.976	20	41
					1155	5
u2d	P2 – H4	0.963	0.978	0.948	25	93
					1158	5
l2r	P2 – H5	0.962	0.979	0.944	24	85
					1160	4
d2u	P2 – H5	0.953	0.969	0.938	37	61
					2167	4
d2u	P1 – H4	0.946	0.934	0.958	153	93
					2060	7
l2r	P1 – H4	0.943	0.963	0.923	78	85
					1019	5
dgl	P1 – H1	0.942	0.983	0.901	17	46

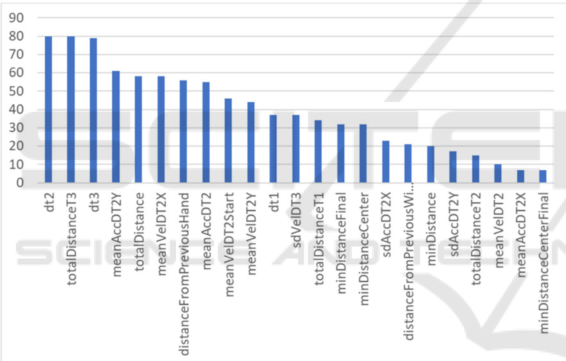

Figure 4: Feature Selection Rate, defined as the number of times each feature is selected in the model, during the training phase with different training sets.

4 RESULTS

Overall, the sensitivity of the proposed models reached high levels (mean 95.35% sd 2.62%), while the specificity varied depending on which healthy subject was used for testing. Subjects H2 and H3 did not fit the created models well (mean specificity 53.14% sd 14.44%), while subjects H1, H4, H5 responded significantly better (mean specificity 86.55% std 7,55%). Of note, when the above pipeline was performed with the exclusion of the H2 and H3 subjects, there was a significant drop in the models' metrics moving from ~95% to ~70%. This indicates that healthy subjects can be heterogeneous, and familiarity with games in general could be a reason behind that. The proposed methods allow for patients to be clustered into categories reflecting similar hand movement patterns as a result of similar neuromuscular disorders/physical trauma.

Performing the above pipeline for all 10 combinations of patient and health training set x 8 movement direction (e.g., right to left) resulted in 80 executions. The 8 best performing models based on the balanced accuracy metric are depicted on Table 1.

The features finally utilized for the creation of each model varied based on the selected direction, and their p values varied also depending on the selected training dataset. Figure 4 shows the selection rate of each feature in the model creation. Out of the 28 features examined, 23 appeared at least once with among the most common being the duration of the Movement (dt2) and Stabilization (dt3) time periods.

Table 2 depicts the features used for the development of the best performing model (direction Top to Bottom, training P2|H1,H2,H3,H5, testing P1|H4).

Table 2: Mean value for each feature per subject group (Patients, Healthy). Adjusted p was calculated using the Mann-Whitney U test.

Feature	Mean P	Mean H	Adjusted p
distanceFromPreviousWindow	46.609	33.702	0
distanceFromPreviousHand	44.59231	34.55598	0
DT1	544.7925	460.2483	0.0036
DT2	712.3987	261.6593	0
DT2	1942.664	3633.71	0
sdVelDT2	37.42379	17.34871	0
meanVelDT2	50.25814	48.66921	0.004
meanVelDT2Start	41.81328	39.13429	0
meanAccDT2	1350.74	1003.941	0
sdVelDT2X	22.48586	10.47494	0
meanVelDT2X	25.97193	20.89285	0
sdVelDT2Y	30.99457	15.26332	0
sdAccDT2X	21.06343	8.583197	0
Feature	Mean P	Mean H	Adjusted p
meanAccDT2X	23.09528	10.6853	0
sdAccDT2Y	27.11824	13.2992	0
meanAccDT2Y	29.69753	14.80098	0
totalDistance	100.5733	92.49089	0
totalDistanceT2	34.64196	14.41555	0
totalDistanceT3	35.84011	60.09226	0
minDistance	2.077342	1.231234	0
minDistanceCenter	3.828137	2.726778	0.0285

Figure 5. depicts a selection of subject/feature/direction combinations over the course of time for the patients during their physiotherapy. It translates to 9 months for P1 and 6 months for P2. Significant spikes (top left) in certain features can probably be attributed to the changes in the difficulty settings in which the games were played. In all cases, the features that were found to be statistically significant, tended to improve over time towards the values that the healthy subjects had achieved. Some patient's features show a steady improvement, at least regarding the data collected thus far, (bottom right, dt1). On the contrary, other features seem to reach a plateau over time (bottom left meanVelDT2Start) but at the same time not reaching the performance of healthy subjects. Whether this plateau is unsurmountable and characterizes the nderlying pathology, or some movement characteristics require more effort in order to improve over a certain point (top right), remains to be investigated.

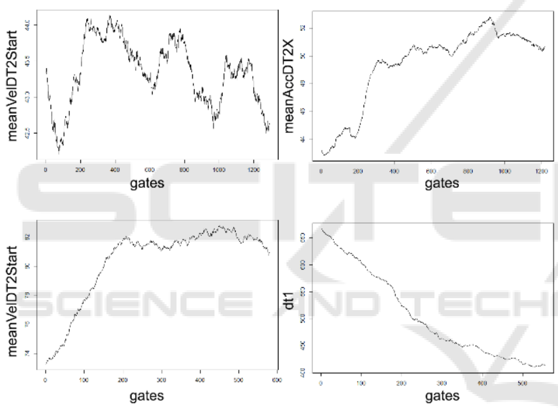

Figure 5: Features' trend over time. X-axis depicts the gates the subject has played in chronological order. Top left subject:P1| direction: u2d|feature:meanVelDT2Start. Top right subject:P1| direction: l2r|feature:meanACCDT2X. Bottom left subject:P2| direction: l2r|feature:meanVelDT2Start. Bottom right subject:P2| direction: ud2|feature:DT1.

Table 3 shows the final classifiers' performance when used on the external data that was P3. The classifiers achieved over 90% accuracy in identifying P3 as patient for 6 out of the 8 directions while the remaining two where in the high 80%.

Table 3: Results of the final classifiers on the external dataset (P3).

Movement type	Total Gates	Correct Gates	False Gates	Accuracy
u2d	258	243	15	0.94186
l2r	234	215	19	0.91880
r2l	224	200	24	0.89285
d2u	245	230	15	0.93877
diag1	147	137	10	0.93197
diag2	150	137	13	0.91333
diag3	144	136	8	0.94444
diag4	136	119	17	0.875

5 DISCUSSION

The detailed analysis presented in this work is based on a system that extends the use of Leap sensor for upper extremity's functional rehabilitation exploiting the quite precise detection that is provided.

Although there is distance to cover in the field for gamification approaches such as ours to reach their full potential as GaaHS, the presented results are promising and novel. Specifically, the presented approach stands out since it attempts to propose and evaluate quantified metrics regarding not only the in-game performance but also the hand motion characteristics which reflect the underlying pathology.

Looking at the score-based characterisation vs movement-feature based classification, patients P1 and P2 achieved scores comparable to healthy subjects, while P3 had significantly lower scores than all the other subjects. The values of P3's features were further away from the healthy subjects than the rest of the patients. This indicates that a single score of success or failure in undertaking a task is not always enough for a successful classification in the GaaHS scope. On the other hand, the proposed classifiers using movement features that carry a higher degree of information, were able to distinguish between healthy and pathological movement.

One of the challenges that we encountered during this research was the parametrization of the game scenario which translates to a varied range of motor control exercises. The main problem was that introducing several variables would introduce a high degree of complexity and decrease the comparability of the data. Furthermore, a major challenge is the mapping of the game-specific features to generalized concepts that are applicable in other scenarios.

Considering the limitations of the study, while the number of gates is high the number of patients and healthy subjects is low in terms of variability within the population. While this can be understood for this methodological study, a future wider study would be useful to provide a more concrete evidence and provide the correlation with the patients' medical data and progress as recorded by the physician. In these next steps, the analysis will take into account the effect that settings with different difficulty may have on the result. The familiarization with the specific game as well as the subject's general aptitude with video games, is something that can affect the subject's performance, and needs also to be considered.

Furthermore, while the motion specific classifiers (horizontal, vertical, diagonal) are useful in terms of detailed characterization, a unification of the classifiers will also be helpful in a clinical context, providing an answer for a subject's clinical image regarding hand mobility as a whole and not divided in specific directions.

6 CONCLUSIONS

This analysis has shown promising results during the classification process especially as far as the patients are concerned, the inconsistencies in the performance of the healthy subjects can be attributed to the heterogeneity of the healthy population. Additional data will help in establishing a broader healthy baseline. In general, the patients were slower in their reaction time and had a greater distance from the gate center compared to the healthy subjects.

Regarding future goals, our main objective is the quantification of patient's progress and effort will be placed on matching their progress as indicated by our features to the commonly used scores regarding upper limb mobility, such as FMA-UE (Singer and Garcia-Vega, 2017) and FIM (Hamilton et al., 1994).

Next steps will also involve the level of difficulty in the analysis and define the optimal settings for patients that share common characteristics. Moreover, more complex feature extraction methods will be explored. Expanding the dataset both in terms of games and in subjects will facilitate a more robust statistical analysis and additionally will allow us to explore the clustering of patients based on their performance and progress.

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