# On Using Controller Input and Signal Processing as a Parameter for Learning in CPHS

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**Abstract:** With the emergence of safe autonomous vehicles and systems, there is a demand for creating systems that are aware of and responsive to the human. There have been decades of work dedicated to human-in-the loop studies. However, when it comes to human-aware systems that are responsive to the human based on learning parameters, there is a need for the appropriate input parameters to assess learning. In this work, signal processing methods were used to analyze game controller input signals in response to humans completing a simulated quadrotor landing task with three levels of difficulty (easy, medium, and difficult) over 30 trials. Data collected from twelve adults were analyzed using energy of the controller input signal; 2) non-dimensional velocity; and 3) dominant frequency analysis. The landing trajectories were also mapped graphically revealing three categories of learners: beginner, intermediate, and trained. The results from the signal processing analysis procedure provided supporting evidence for these categories. The results of this work suggests that input parameters from a game controller can be used as a proxy for learning and can provide an additional means for enabling human aware systems.

*Keywords:* Simulator controller, signal energy analysis, dominant frequency analysis, learning process

## 1. INTRODUCTION

Automation is being implemented in numerous contexts such as automobiles, drones, and agriculture. While many of these will be shared by multiple users with distinct usage patterns, the automated systems have to learn these patterns and ensure that individuals are performing as they should. Such responsiveness of the the machine to humans enables successful integration with the environment.

In order to develop human-aware machines that are responsive to humans, capturing behavioral data is important. Behavioral data comes in many forms including self-report, observed actions (e.g., mouse clicks, keystrokes, and other gestures), and other intention based responses (Khan et al. (2008); Cepeda et al. (2019); Broota (1989)). However, very few studies have documented to the use of input from game controllers as a tool for capturing behavioral data.

Game controllers have proven to be useful tools to capture continuous behavioural data (Markey et al. (2010)). The game controller data was found to be useful in analysing interpersonal behaviour with higher reliability. Within a time series, it can provide high resolution information about the nature of fluctuations also (Sadler et al. (2009)).

The game controller data helps us to conduct cross correlations, cross spectral analysis and other time series techniques (Warner (1998)). Psychological constructs can be measured as continuous time signals using game controllers (Boker (2002)) which can be used in nonlinear dynamics models (Maxwell and Boker (2007)).

The flow of information between brain parts related to cognitive, sensory and motor processes are parallel and continuous. Recording continuous responses can help us study multiple mental activities and their transitions states. Continuous responses provide a more realistic data collection method also, for a wide variety of participants. Discrete controls can cause confusion related to response-key mapping and deviate the user from the actual objective, which lead to less useful data.

The continuous input game controller used in the experiments helps the user to interact continuously with a simulator, compared to a keyboard with discrete keystrokes. Apart from the standard behavioural patterns, the controller usage data provides additional information about the trajectories and learning paths. Continuous data from controllers can provide high resolution spatio-temporal information about the time-evolution of cognitive processes, changes of mind, error corrections and subjective confidence.

As a preliminary study, we devised an experimental approach to quantify the learning curve of human subjects in using a new drone simulator. We focus on the user input data and their performance to evaluate their progress in learning. The drone simulator uses a game controller similar to a flight control.

# 2. EXPERIMENTAL METHOD

### *2.1 Set-up*

The experiment consists of a Python based 2D drone simulator (Figure. 1) and a game controller used in flight simulators (Hotas Thrustmaster 4). The simulator is run on a PC monitor with a resolution of 1920x1080p at a refresh rate of 60Hz. The game controller is operated using both hands. The left hand is used to control the throttle (up-down motion) and the right hand is used to control the roll motion. The drone does not have any pitch or yaw motions.

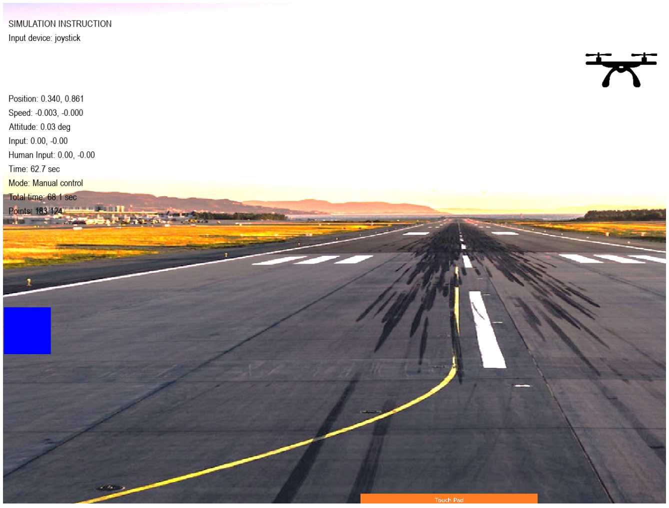


Fig. 1. The 2D drone simulator used in the study

### *2.2 Methodology*

The experiment was conducted in normal indoor lighting. The participants were asked to land a quadrotor on a landing pad where the drone default starting location was in the upper right corner of the screen. Three scenarios (easy, medium, difficult) were presented in random order and each scenario was run 10 times. The participants were given 4 trials before the experiment on the easy level. The medium and difficult levels had an obstacle near the landing pad. Relaxing music was played for 25 seconds between the runs to bring the subject back to a reference state. The quadrotor was programmed to have both linear and angular momentum to make the dynamics more realistic.

### *2.3 Selection of participants*

A total of 15 people participated in the study. However, the data from 3 participants had recording errors, but the remaining 12 were used in the analysis. The Purdue IRB approved this study. All the participants had normal or corrected-to-normal vision. Each participant was given 4 trials before the experiment. The average age of the participants was 26.2 years (range 21-35 years) with a standard deviation of 5.04 years. Of the 12, 9 were men and 3 were women. There were 2 participants without a driver's licence. There were 3 participants who play video games daily, 2 who gamed weekly and the rest of the group had minimal or no gaming experience. Most of the participants reported that they had the highest stress level during the first set of runs. The trust and confidence values were recorded by the participants on a scale of -10 to 10 after each run. A post-experiment survey was conducted to get overall feedback about the experiment.

# 3. DATA ANALYSIS AND RESULTS

The collected data was de-identified and the participants were categorized as beginner, intermediate and trained users, based on their trajectory data. A smooth, short trajectory where the drone had minimum tilt was used as a reference or baseline trajectory by which all other trajectories were compared. The participants whose trajectories had high deviation ($> 50\%$) from the reference/optimal trajectory for 30 runs were considered as beginner level users (Figure 2) and the participants whose trajectories had less deviation ($< 25\%$) from the reference trajectory were considered as trained users (Figure 3). The participants with trajectories in the intermediate range ($25 - 50\%$ deviation) were considered as intermediate users (Figure.4).

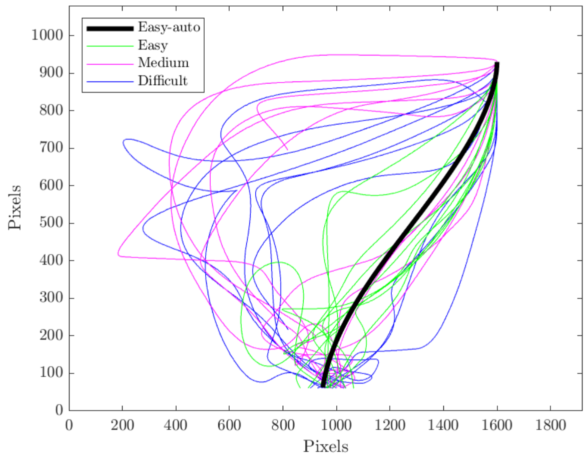


Fig. 2. Trajectory data of a beginner. An optimum trajectory (Easy-auto) for the simplest case is shown for comparison in addition to the higher spatial variation from the optimal trajectory is shown.

### *3.1 Game Controller data*

The input data to the game controller was extracted and analysed. The joy stick data included separate signals for roll and thrust, sampled at 32Hz. The drone simulator was made exclusively for the study and therefore it is a new environment for all participants. It is expected that every participant goes through a learning process while using it. The duration of learning process will be different for the three groups identified. The game controller data was analysed using 3 methods described in as follows to check the progress in learning:

*Energy of the game controller input signal* The energy of a signal is a measure of its capacity to do work and this idea extends to bio sensors also. Energy of a person's audio signals gives a measure of work done by the

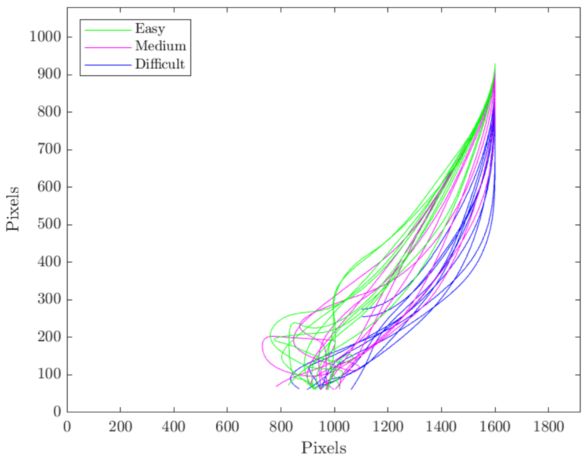


Fig. 3. The trajectory data of a trained user shows less spatial variations.

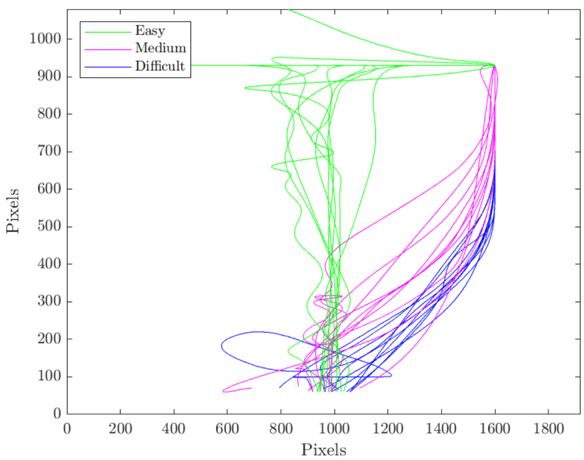


Fig. 4. Trajectory data of an intermediate user.

person to produce that sound (Guido (2016)). Energy is a useful measure as it is conserved in time-frequency domain conversions and it has higher robustness to variations during recording and transmission processes. (Oppenheim et al. (2001)).

The reference trajectory used in the analysis has low controller input. A new user has higher controller data input at the beginning and it reduces with progress in learning. The controller input values stabilizes later to values comparable to the input values to the reference trajectory.

It is assumed that the energy of the controller input signal is proportional to the effort put forth by the user to control the drone. Thus the energy analysis of the game controller input signal can be used as a scalar method to compare the efforts exhibited by the subject in different runs. The energy associated with game controller signals was found to decrease with improvements in learning.

The energy values for all the runs for all participants were calculated. It shows that the controller energy was lower for trajectories similar to the reference trajectory for all 3 levels of difficulty. One example from each category of users was taken to demonstrate the trend in controller energy data.

The controller energy data for each participant was non-dimensionalized using the peak energy value ($E^* = E/E_{max}$, $E^* \in (0, 1]$) from the corresponding difficulty level for evaluating the trend.

Comparing the beginner level (Figure.5) and trained (Figure.6) participants, it can be seen that there is a difference in the trend of normalized energy values over time. The energy values show mostly a steady trend in the case of trained users whereas a decreasing trend is not seen in the case of beginner level users.

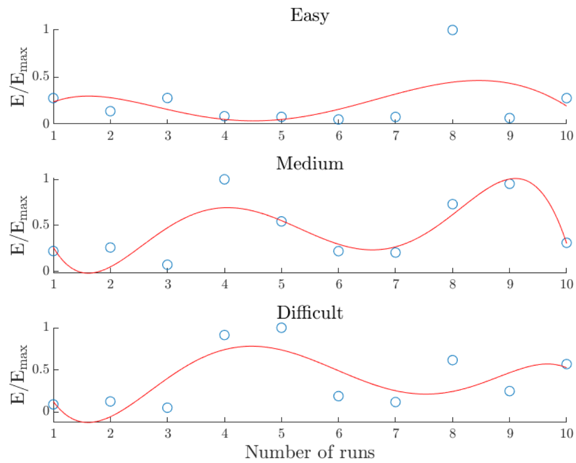


Fig. 5. Normalized energy ($E^* = E/E_{max}$) plots of the game controller input signal for a beginner level user for 3 cases - easy, medium and difficult levels. A fourth degree polynomial fit is used to show the trend of the data

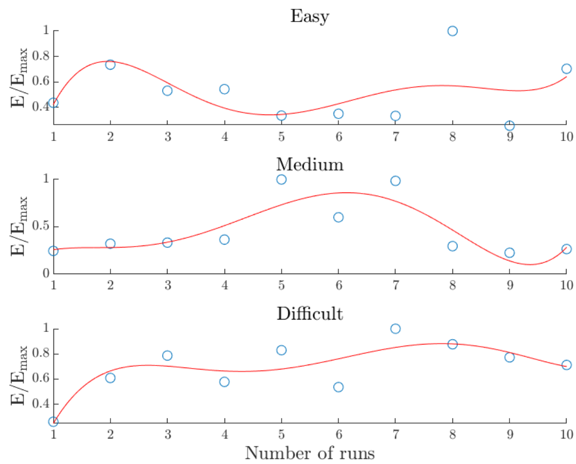


Fig. 6. Normalized energy plots of the game controller input signal for an trained user for 3 cases - easy, medium and difficult levels. A fourth degree polynomial fit is used to show the trend of the data

Compared to beginner level and trained users, the controller energy data of an intermediate user (Figure.7) shows a decreasing trend throughout the experiment. The reduction in controller energy data shows progress in learning within 30 runs. A similar trend was observed for other participants in the intermediate category. Individual subjects appear to have a learning curve that rises from a beginner level to trained level in less than 10 trials (Gallistel et al. (2004)).

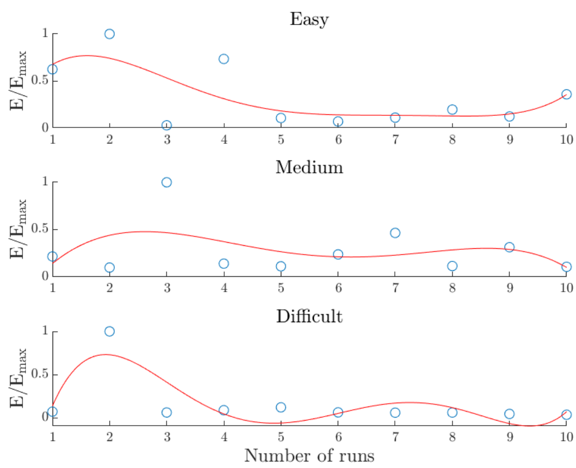


Fig. 7. Normalized energy plots of the game controller input signal for an intermediate user for 3 cases - easy, medium and difficult levels. A fourth degree polynomial fit is used to show the trend of the data

*Non-dimensional velocity* Higher cruising speed of the drone can be taken as another indicator for the confidence of the user. Thus, the peak flight-velocity and variation in flight-velocity can be used to study the progress in the learning process.

The first and third quartiles of flight-velocity for each participant were extracted and non-dimensionalized using their peak value in each difficulty level ($V^* = V/V_{max}$). $V^*$ helps to identify the relative variations within a set of runs for each user and helps to recognize progress in learning. Non-dimensionalization of velocity helps us to compare the spectrum of performances of different users effectively.

The first and third quartile flight-velocities were selected for the analysis, to get a better representation of extreme values of flight-velocity. In an ideal-learning case, the non-dimensionalized first and third quartiles of flight velocity are expected to increase initially, at different scales, and later stabilize with runs. It corresponds to a learning process where the user learns the control and dynamics and, then improves his performance by moving to higher velocities.

While trained users (Figure.9) were found to identify their safe speed quickly and sustain it throughout the experiment, the beginner level users (Figure.8) took more time to reach stable flight-velocity and they have higher fluctuations in their flight-velocity. The stable flight-speed of trained users were steady and higher than other groups, which indicates quick completion of landing task.

For the intermediate users, it can be seen that the third quartile of their flight-velocity decreases over time, showing progress in learning (Figure.10). The variation in the first quartile of flight-velocity for intermediate users shows

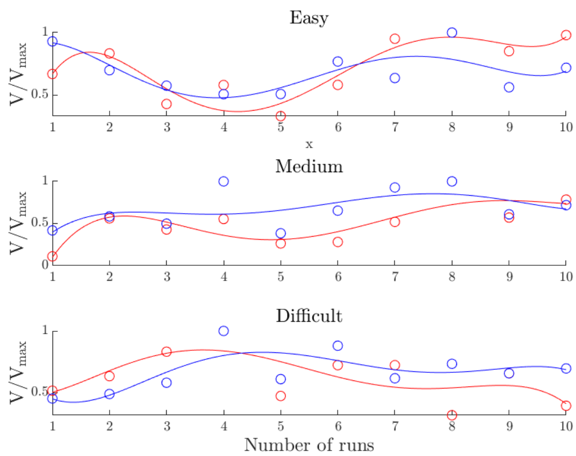


Fig. 8. Plots of the normalized 1st and 3rd quartile velocities of a beginner user for 30 runs

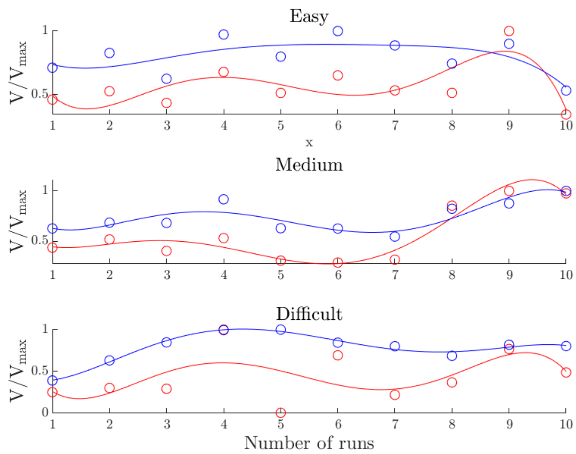


Fig. 9. Plots of the normalized 1st and 3rd quartile velocities of an trained user for 30 runs

a similar trend with a slower rate than the third quartile of the flight-velocity.

*Dominant Frequency Analysis* Dominant Frequency Analysis is a method used to quantify change of a fluctuating signal. In patients with persistent atrial fibrillation, a reduction in the dominant frequency of heart beat indicates sufficient eradication of drivers of atrial fibrillation/abnormal heartbeat (Yoshida et al. (2010)). Dominant frequency analysis can be applied to complex signals with varying amplitude and morphology and it is mostly robust against noise, especially with highly regular activation intervals (Ng et al. (2007); Ng and Goldberger (2007); Latchamsetty and Kocheril (2009)).

The dominant frequency of the controller input signal for each run was calculated and the trends were plotted against the runs. It is assumed that the dominant frequency of the controller input signal is a characteristic of the gaming style. Higher values of dominant frequency corresponds to quick controls and lower values corresponds to slow controls.

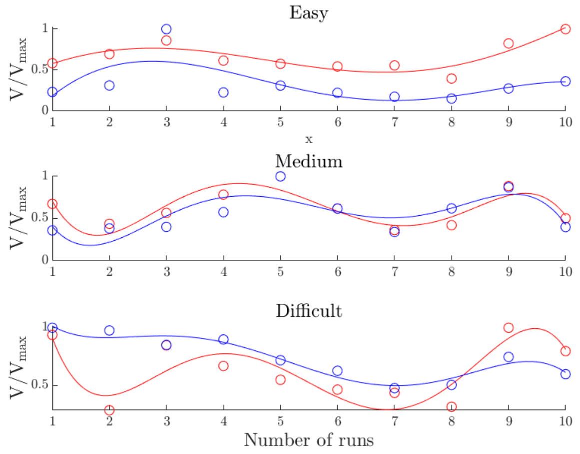


Fig. 10. Plots of the normalized 1st and 3rd quartile velocities of an intermediate user for 30 runs

As expected, the overall trend shows trained users have higher values for the dominant frequency and the beginner level users have lower values for the dominant frequency. The intermediate users (Figure.13) have dominant frequencies with values between that of trained (Figure.12) and beginner level users (Figure.11).

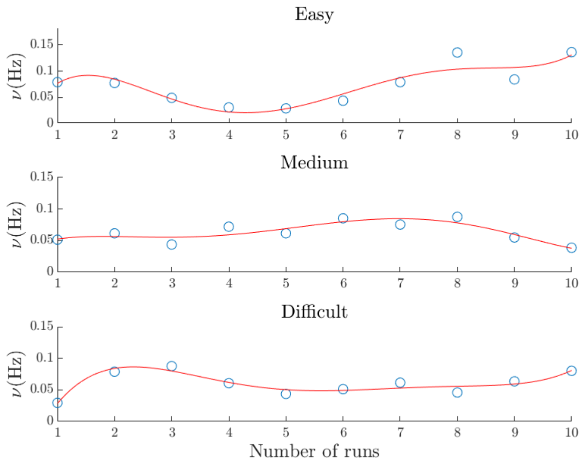


Fig. 11. Plots of the dominant frequency of the controller input signal for different levels of difficulty for a beginner level user.

It can be seen that the frequency variation in the case of beginner level users and trained level lessen over multiple runs. These users appear to have less variation in their gaming style. But in the case of an intermediate user, it can be seen that the values oscillate with respect to a mean value and the fluctuation decays with more runs. This suggests that the intermediate users tested different gaming styles and finally learned a successful style. Thus the Dominant frequency analysis verifies the learning process we have observed in the case of intermediate users and also help us converge on the idea of using controller input signal for quantifying learning process.

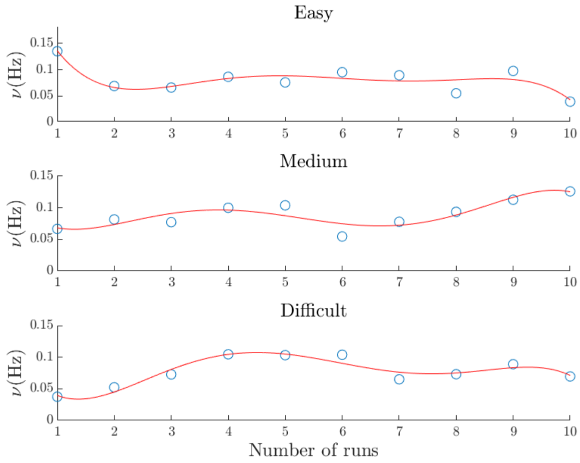


Fig. 12. Plots of the dominant frequency of the controller input signal for different levels of difficulty for a trained user.

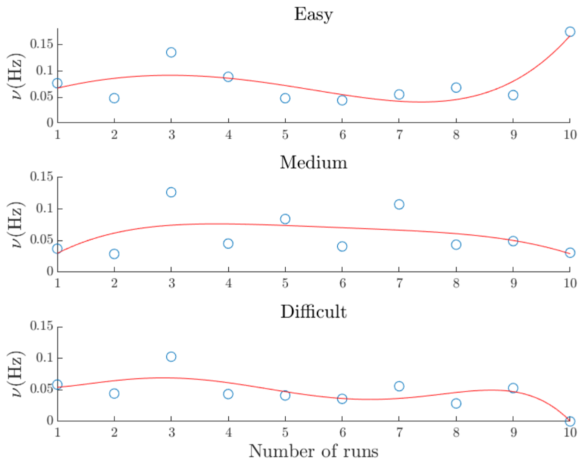


Fig. 13. Plots of the dominant frequency of the controller input signal for different levels of difficulty for an intermediate user.

## 4. CONCLUSIONS AND FUTURE WORK

The study aims at quantifying the learning process of users on a 2D drone simulator using controller data. The performance data of different users were analysed to check potential indicators to represent progress in learning over a short period of time. The users were divided into 3 groups namely beginner, intermediate and trained users, based on their gaming experience. The users who were able to master the game in 30 runs, even though they had less gaming experience, were considered as intermediate users.

The game controller input data was extracted and the trends in the energy of the signal were analysed. It appears that, for an intermediate user, the energy of the controller input signal reduces over time. The energy associated with the game controller input is directly related to the efforts exhibited by the user to control the drone. The difference in energy of the game controller input signals between one of the optimal trajectories and a user trajectory can be taken as a measure of learning.

Comparison of game controller data between user trajectories and an optimal/reference trajectory can be used to determine the experience level of a participant. The analysis can also be used to determine the duration of the training required for a beginner level user for a new task.

The cruising velocity of the drone was another factor considered in the study. While trained users reached higher, stable cruising velocities in less time, the beginner level users had high fluctuations, the intermediate users showed a diminishing trend, reaching a steady value towards the end of the experiment. Identifying a safe cruising velocity also can be considered as an indicator for learning.

The Dominant frequency analysis of the controller input signal helped us verify the learning process by analysing the variation in the dominant frequency of the signal over time. The intermediate users exhibited a converging gaming style where they started with high frequency inputs, reduced it over many runs, reaching stable values towards the end. Starting from a fluctuating gaming style and reaching a stable style can be taken as a sign of learning.

An important contribution of this work is the use of signal processing methods on game controller data to identify systematic behavioral results of participants. The use of game controller input signals provides an additional means for enabling human-aware systems. Three categories of participants were identified as well as the group that had maximum learning in the given time. The results of this work suggest that controller input can be used as a proxy for learning. Future work involves conducting additional studies in different scenarios to validate these observations.

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