Investigating Complex Dynamics in Eye-Aspect-Ratio of Expert Tetris Players Using Recurrence Quantification Analysis: 2025 IEEE Conference on Games (CoG)

Investigating Complex Dynamics in Eye-Aspect-Ratio of Expert Tetris Players Using Recurrence Quantification Analysis

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***Abstract*—Expert video game players exhibit unique behaviors compared to their less experienced counterparts. Such behaviours may also influence physiological aspects such as blinks and eyelid movements. In this study, we used the Eye Aspect Ratio (EAR) signal from a webcam to investigate the complex dynamics of eyelid movements among players with different levels of expertise in Tetris. We measured complex dynamics using recurrence quantification analysis (RQA) based measures (Determinism, Laminarity, Average Diagonal Line, and Trapping Time). Our results show that expert Tetris players display more complex patterns in their eyelid behaviour, but also that some of the measures obtained using RQA correlate directly with player actions (keys pressed) and events in Tetris (numbers of lines cleared). This study provides the first example of a direct connection between RQA measures extracted from the EAR signal and behavior displayed in a game. Our results also demonstrate the potential of using RQA measures extracted from the EAR in analysing human behavior during other screen-presented tasks.**

***Index Terms*—Video games, Tetris, Expertise, Eye Aspect Ratio, Complexity, Blinks, Recurrence Quantification Analysis**

I. INTRODUCTION

Tetris is a famous video game and has been popular since its introduction in 1985. One of the elements of this success is the simplicity and intuitiveness of the game's mechanics– anyone can play Tetris with minimal effort put into learning them. The player has to place Tetrazoids (the tiles falling from the upper part of the game environment, henceforth zoids) to clear lines and accumulate higher scores. In Tetris, you can rotate, translate (left and right movements), or increase the rate of the drop of the zoids. The other element of Tetris's success is that mastering these simple mechanics is not enough to master Tetris. To play at higher difficulties, when zoids fall faster, players have to automate many of their decisions and find ways to facilitate high-speed decision-making under uncertainty. This involves a complex interplay between manual dexterity, perception, and cognition. High-level players behave very differently from novices, which can be captured by the decisions they make in-game [3], but also at a physiological level [4]. Perhaps for this reason, Tetris has been used to investigate, for example, working memory [1] and fluid intelligence [2]. That said, this feature of Tetris lets high-level players interested in mere play to constantly challenge themselves by obtaining higher scores until, in rare cases, they manage to 'break' the game.

Generally, expertise in video games has been extensively investigated [5]. Specifically, Tetris expertise manifests in decisions about zoid manipulation [6] and strategies that overcome performance plateaus [3]. Interestingly, these behavioral markers of expertise emerge during the earliest phases of the game, during level 0 and level 1 [3], [6]. Moreover, specific expert-related traits are not limited to in-game behaviors but also extend to physiological aspects. For example, previous studies employing Tetris have shown that experts display differences in eye blinks compared to their less experienced counterparts [4]. Furthermore, differences in blinks between experts and novices were not only found in Tetris, but also in games such as Hearthstone [7], in serious games such as The Sustainable Port [8], and in real-life scenarios, such as suturing a wound [9].

Previously mentioned studies use methods that extract blinks non-invasively from webcam recordings [4], [7], [8]. More specifically, they extract the Eye-Aspect-Ratio (EAR) for each frame of the video, which is a measure used to track the distance between the upper and lower eyelids obtained from generated landmarks. Together, EAR provides a time series signal that contains the distance between the eyelids, where the peaks represent the blinks in the signal. This makes the EAR signal similar to other physiological signals, such as the Electroencephalogram (EEG) and the Photoplethysmogram (PPG) (see Fig. 1). EEG and PPG recordings are often used to extract physiological temporal and spectral information. These signals also contain complex dynamics that can be detected using tools from the science of complex systems, such as Recurrence Quantification Analysis (RQA) [11], [12]. To our knowledge, RQA has not yet been applied to EAR.

RQA measures and quantifies recurrent states and self-similarities within a signal. For example, a signal with many similar patterns re-occurring over time would score higher on RQA measures than a signal with fewer re-occurring patterns.

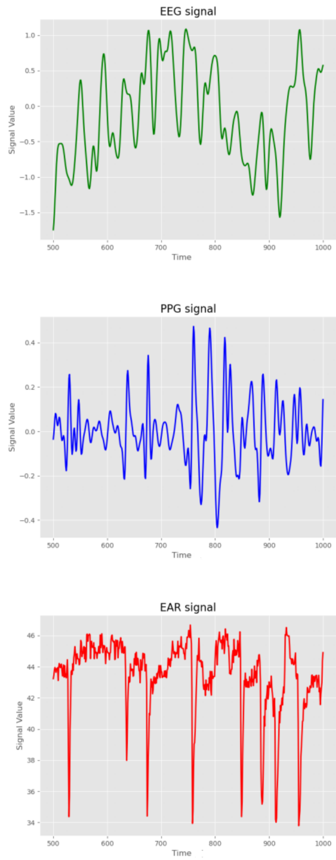

Fig. 1. Examples of EEG, PPG, and EAR. All three signals show peaks and variations. The EEG signal was extracted from an open-source dataset [10], while the PPG signal comes from the same data as used for this work.

A strong advantage of this method is its robustness to noise in the signal and no need for further mathematical assumptions in modeling and transformation of the signal [15]. For these reasons, RQA has been used with a variety of signals to identify complex dynamics in EEG data [12], [13], PPG data [11], and Electrocardiogram (ECG) data [14]. In our case, we use the EAR signal, which is similar to PPG and EEG (see Fig. 1), and then straightforwardly apply RQA to it to identify complex dynamics, focusing on finding differences between expert Tetris players and less experienced players. Therefore, the main research question of this work is the following: *To what extent can RQA-based measures extracted from the EAR signal be used to identify players with different levels of expertise in Tetris?* Furthermore, we investigate whether there is a relationship between the actions performed during gameplay, the number of lines cleared, and the RQA-based measures (Determinism, Laminarity, Average Diagonal Line, and Trapping Time). Following the results of other studies that used eye-tracking data to investigate expertise in real-life [16], [17], we expected expert players to exhibit more complex dynamics, which would be reflected in the EAR signal being less predictable and less deterministic. Whatever we learn here about EAR and its complex dynamics in relation to expertise will build on what we already learned about more basic features of eye movements and their connection to expertise, reported in other studies [4], [7]–[9]. Apart from insights into player behavior and expertise, our contribution is also methodological, in that to our knowledge ours is the first study that applies RQA to EAR.

II. Related Works

A. Tetris, Expertise, and Blinks: an Overview

Tetris has been extensively used in the last 30 years to investigate expertise [18]. Many studies investigated the behaviors that expert players exhibit during Tetris. For example, earlier research by Manglio et al. [18] focused on epistemic actions, i.e., actions that can be performed to unload the workload by, for example, rotating the zoids several times. Such actions are exploratory and are used to detect which location may be the best to place zoids. However, more recent research [19], [20] showed that expert players tend to reduce the number of rotations when performing zoids placement. This may be explained by the extra time that extra rotations require, which may impede players to obtain higher scores when the fall speed of the zoids increases in harder levels.

More recently, studies showed that expert players tend to adopt specific strategies to, for example, overcome performance plateaus and obtain higher scores compared to their less experienced counterparts [3], [6]. Such studies were performed extracting zoids-related features using a Python-implemented version of Tetris, but also by simply looking at the keystrokes pressed during an initial phase of a Tetris game session [20]. Interestingly, these results from different studies seem to converge to the idea that expert Tetris players display specific behaviors in zoids' manipulations already during level 0.

A previous study demonstrated that Tetris players not only exhibit specific in-game behaviors, but also specific physiological variations when looking at their blink rate per minute in both their complete gameplay and at level 0 [3]. This study showed that expert Tetris players, compared to less experienced players, displayed lower variations in blinks/m from their blinks/m at rest. This difference already emerged during level 0, during the first minute of gameplay. Since experts are generally highly competent individuals, such results may be related to the relationship between performance and expertise. This connection may be justified by previous results showing that people who perform well on a go/no-go task exhibited more blinks per minute compared to people who did not [21]. Such aspects may be due to the connection found between blinks and activity in brain areas such as the striatum and the prefrontal cortex; areas strictly connected with goal-directed behavior and performance [22].

B. Blinks, eye movements, and EAR signal

As stated above, blinks have been connected to performance and expertise in multiple studies, primarily by analysis of their frequency, duration, and similar statistical features. Human beings have an average blinks/m rate between 15 and 19 [4]. Performing specific tasks leads to alterations of blinks/m.

For example, having a conversation [37] tends to increase blinks, while visually demanding tasks such as reading and playing video games tend to reduce the number of blinks [4]. However, when tracking signals containing blinks, such as the EAR previously conveyed, other information is still present in the signal. Such information may extend beyond blinks, their duration, and their intervals, and it also includes movements of the eyelids. Several of these movements occurring in the eyelids are caused by muscles involved in the eye movements. For example, the Oculomotor Nerve is in charge of muscles responsible for the eye movements, such as the medial rectus, superior rectus, inferior rectus, and inferior oblique, but also of the levator palpebrae superioris, i.e., the muscle elevating the upper eyelid [38]. Furthermore, other studies found connections between eye movements like saccadic, sudden eye movements [39], and pursuits, smooth eye movements aiming to follow an object [40], and eye blink. For example, it was found that the number of blinks increases while saccades occur, as this process may help reset the visual system [39]. In general, blinks were found to influence the kinematics of saccades, such as their duration, maximum acceleration, and maximum deceleration [39]. These complex phenomena, connected to blinks but also eyelid movements, may be tracked using non-linear methods such as RQA, which aims to detect complex dynamics in biological signals such as the one presented in the EAR.

III. Methods

A. Data Collection and Expertise Definition

For this experiment, we involved 80 participants at Tilburg University (40 males, 39 females, 1 nd, *M*age = 27.27, *SD*age = 5.92). At the beginning of the experiment, the participants were asked to sign an informed consent form and to provide demographic information and their self-assessed experience with Tetris on a Likert scale between 1 and 5 ('not experienced at all' up to 'very experienced'). After this, the participants started the experiment. We recorded videos of the gameplay and the faces of the participants using the Open Broadcast Software (OBS); all the videos used a frame rate of 30 fps. This process was carried out to use, at a later point, the participant's face to extract the EAR information. After this, the participants were given two minutes to try the keys to play the NES version of Tetris on the laptops used for the experiment (Z for the counterclockwise rotation, X for the clockwise rotation, and left and right for the left and right translation, respectively). During this period, participants were also informed that they could use the information available in the "next" square of the game environment to start thinking about where to place the upcoming zoid (Fig. 2). After this two-minute period, the actual Tetris session started. The participants were not informed about the duration of their gameplay to avoid them tracking time; the gameplay for each player lasted 13 minutes. Every time a player lost a match, they were asked to restart from level 0. Information about the keystrokes used to play the game were collected using the RUI software [23] as done in another study employing Tetris to study expertise [20]. At the end of the experiment, the number of lines cleared by the participants were manually counted by the experimenters watching participants' gameplay recordings.

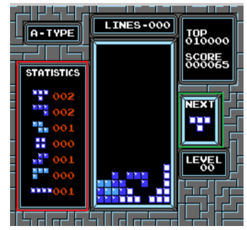

Fig. 2. The NES Tetris environment during the gameplay. In the red square the "statistics" information, while in the green one, the "next" zoid information.

After data collection, participants were clustered in groups based on the number of completed matches in the 13 minutes of gameplay [4], [20] (*M* = 2.76 matches, *SD* = 1.88) and the average score obtained across the 13 minutes of gameplay (*M* = 4291.93, *SD* = 6771). Before proceeding with the clustering process, using a k-means algorithm, the average score was log-transformed, given its skewness [24]. Using these two variables, k-means found 3 optimal clusters based on the elbow method. As a result of the clustering process, three groups of players with different expertise were defined (Expert, Intermediate, and Novice). 22 participants belonged to the Novice group (Males = 11, Females = 11), 38 to the Intermediate group (Males = 17, Females = 20, nd = 1) and 20 to the Expert group (Males = 12, Females = 8). These 3 groups not only represented different average scores and number of matches, but also differences in the self-assessed Tetris experience (see Table I). The sample used for this study was the same as the one presented in two previous studies focusing on blinks variations [4] and early prediction of expertise using the keys pressed by the players [4], [20]; more information about the sample and the clustering process can be found in these two studies.

TABLE I
A table conveying the number of Tetris matches played, the average score obtained, and the self-assessed level of experience for the three groups of players.

	Novices	**Intermediates**	**Experts**
Matches Played	5.22 (SD = 1.41)	2.32 (SD = 0.86)	1.1 (SD = 0.30)
Average Score	305.69 (SD = 147.07)	1483.26 (SD = 971.14)	14013.45 (SD = 7556.00)
Tetris Experience	1.73 (SD = 0.69)	2.21 (SD = 0.87)	2.80 (SD = 0.75)

B. EAR Extraction

As conveyed in previous studies [4], the EAR signal provides information about the distance between the two eyelids. This signal can be tracked using specific facial landmarks available in the FaceMeshDetector available in cvzone, a Python library. Each couple of landmarks is used to define six points projected on the participant's face and then used to extract the EAR (see Table II). Once these six points are projected on the participant's face, the following formula: `(|P2-P6|+|P3-P5|)/(2|P1-P4|)` is used to track the distance between the eyelids across the frames. The distance across the entire recording generates the EAR signal. Such a signal was used in the past to track blinks [4] and other features related to blinks, such as the average duration and intervals [8]. The process of EAR signal extraction was employed for all the participants, creating a .csv file. This process generated 80 EAR-signals, 13 minutes long, at 30 fps, corresponding to 23,400 frames (13 minutes times 60 seconds times 30 frames).

TABLE II
POINTS TO DETECT THE LEFT AND RIGHT EYE USING THE FACEMESHDETECTOR

Point	Left Eye	Right Eye
P1	243	385
P2	22	252
P3	24	254
P4	130	463
P5	160	387
P6	158	359

C. Recurrence Quantification Analysis

Before extracting the RQA measurements, a few preliminary steps must be performed. These steps are the phase space reconstruction and the creation of recurrence plots.

1) Phase Space Reconstruction: A phase space reconstruction (PSR) is needed to determine the dynamics that characterize the signal. PSR requires two main parameters, namely the number of delays and the number of dimensions to unfold the complex dynamics of the signal. These parameters allow the PSR to correctly define the behavioral and temporal evolution of the signal before applying RQA to the time series data. One of the approaches to perform this procedure is to use time-delay embedding [25]. When applying the time-delay embedding, it is crucial to specify the delays, which represent the number of times lags to generate temporally shifted copies of the original signal. Another relevant aspect is the number of embedding dimensions; these dimensions are used to unfold the higher-dimensional dynamics characterizing the signal. Besides these two essential parameters, we need to determine the number of recurrent points: points where the signal appears to be in the same state. One solution is to apply a fixed recurrence rate of 5% as suggested in previous studies [26], [27], and some Python libraries like Pyunicorn [28]. This approach was found to be effective when analyzing different signals, providing a robust solution for different numbers of embedding dimensions.

In our data, to determine the number of recurrent points, we used a fixed recurrence rate of 5% as suggested in previous studies [26], [27], while the number of delays and the number of embedding dimensions were defined using, respectively, the average mutual information function [29] and Cao's method [30]. The mutual information function is used to detect the optimal value of delays. This is done by finding the local minimum after which the average mutual information remains constant [31]. On the other hand, the optimal number of embedding dimensions, defined according to Cao's method, aims at finding the minimal number of dimensions to capture complex dynamics in a system given a specific delay value. Cao's method has two parameters to check in order to determine if a time series is chaotic or represents complex behavior: E1 and E2. E1 provides information about the optimal saturation value (optimal number of embedding dimensions), while E2 is used to ensure that the data are not stochastic but deterministic. According to Cao [30], in E2 there should always be at least a dimension not equal to 1 in order for the signal to be deterministic and not chaotic. The converging point of these two parameters (E1 and E2) represent the number of optimal dimensions for the embeddings [30] (See Fig. 3 for an example).

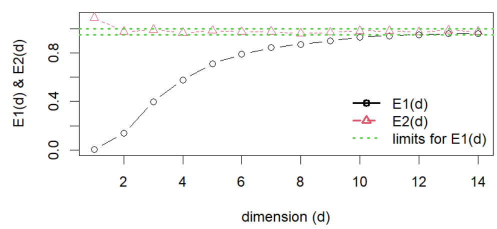

Fig. 3. The Cao's Method to find the optimal number of embedding dimensions. The threshold for convergence was set to 0.9 as shown in an example in the tseriesChaos in R. As the image shows, for E2 there is at least one dimension for which E2 is not equal to 1, and therefore the EAR signal is not chaotic.

We examined a few participants in our data belonging to the 3 groups defined (Novice, Intermediate, and Expert). We found that most of the participants had an optimal delay between 7 and 9, while the optimal number of dimensions tended to converge to 10 independently of the delays used. When running RQA, it is relevant to define a stable number of embedding dimensions and a stable number of delays across all the data; we therefore set the number of optimal dimensions to 10 while the optimal number of delays was set to 8 with a fixed recurrence rate of 5%. This approach was adopted following the methodology conveyed in a previous work [32]. The parameters, delay and number of embedding dimensions, were respectively estimated using the mutual() function in the tseriesChaos package [33] and the estimateEmbeddingDim() in the nonlinearTseries package [34]. Both of these packages are available in R. The RQA measures were extracted using the Pyunicorn library in Python [28]. The Pyunicorn library was used since it was faster and less computationally expensive compared to the options offered in R.

2) Recurrence Plot and Extractable Information: The defined parameters were used as input to generate recurrence plots (RPs, see Fig. 4). The RP offers a visual representation of the dynamics, patterns, recurrent structures, and recurrent states occurring in the signal under analysis. In this study, we extracted four relevant recurrence quantification analysis measures suggested in previous studies [12], [35], [36]. Such measures are:

- **Determinism (%DET)**: This measure refers to the percentage of points lying adjacent in the RP. It provides information about the predictability of the system, where higher percentage values are specific to highly predictable systems.
- **Laminarity (%LAM)**: Similar to %DET, this measure provides information about the points lying vertically on the RP. It provides information about how often the system revisits a specific state.
- **Average Diagonal Line (ADL)**: This measure represents the mean length across all the diagonal lines present in the RP. It provides general information about the time required for the system to transition from one state to another.
- **Trapping Time (TT)**: The trapping time is the mean length of the vertical lines present in the RP. Generally, the higher the TT, the longer a system remains in a specific state.

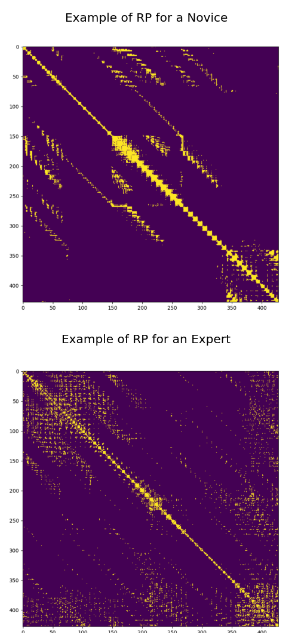

Fig. 4. An RP for a Novice player and one for an Expert player. The RP is based on 500 frames of recording to show examples of the dynamics occurring in the signal. The RP is divided diagonally by the Line of Identity, and the two sides provide the same information, given that RQA is applied to find self-similarities in the signal.

Generally, low values in the above-listed measures are associated with systems displaying high complexity [35]. Such systems are less likely to exhibit sustained and predictable behaviors, spending less time in a specific state. These characteristics are common in systems displaying a faster adaptability to the environment.

D. Analysis Pipeline

Analyses were carried out in this work to evaluate the relationship between the extracted RQA measures and the three groups. Firstly, we ran an ANCOVA analysis where we used the three defined groups (Novice, Intermediate, and Expert) as independent variables while the number of blinks performed during gameplay, extracted using the Isolation Forest with filtering introduced by [4], was used as a covariate. The dependent variables were the RQA measures extracted. This approach was used to ensure that the variation between groups in the RQA measures was not due to the number of blinks performed throughout the gameplay. These analyses were carried out after evaluating the homogeneity of variance with Bartlett's test [41] and the normality of the residuals with the Kolmogorov-Smirnov test [42]. Post hoc corrections were run using a Benjamini-Hochberg test, which gives an acceptable balance between power and controlling for false positives [43]. Secondly, we evaluated the correlation between the keys pressed, the lines cleared, and the RQA measures to investigate whether there was a direct relationship between the measures investigated and the actions related to performance and expertise in the game.

IV. Results

A. ANCOVA Results: Levels of Expertise and RQA Measures

By looking at Fig. 4, one can see differences in the recurrence plots of participants belonging to the different groups. More specifically, we can see Experts having more complex patterns compared to their counterparts with fewer thick lines and more scattered points in their RPs. The three groups also present different values in the four measures used for this work (see Table III). We found these differences to be significant after applying an ANCOVA analysis (see Table IV).

TABLE III
THE VALUES OBTAINED ACROSS THE 3 GROUPS FOR THE CHOSEN RQA MEASURES

	Novices	**Intermediates**	**Experts**
%DET	*M* = 0.64 (*SD* = 0.08)	*M* = 0.64 (*SD* = 0.11)	*M* = 0.56 (*SD* = 0.12)
%LAM	*M* = 0.76 (*SD* = 0.06)	*M* = 0.76 (*SD* = 0.08)	*M* = 0.70 (*SD* = 0.10)
ADL	*M* = 3.22 (*SD* = 0.38)	*M* = 3.38 (*SD* = 0.56)	*M* = 2.92 (*SD* = 0.41)
TT	*M* = 4.11 (*SD* = 0.56)	*M* = 4.25 (*SD* = 0.83)	*M* = 3.66 (*SD* = 0.63)

After applying a post hoc correction, it was discovered that Experts have significantly lower % LAM compared to intermediates (p = .04) and novices (p = .04), while no differences were found between intermediates and novices (p = .90). Similar results were found across the other three measures considered. In the case of %DET, where there was no significant difference between Novices and Intermediates (p = .99) but a significant difference was found between Experts and Novices (p = .03) and Experts and Intermediates (p = .03). For the remaining measures, the same results were found when considering the TT and the ADL; both of them proved to be statistically significant. No significant differences were found between Novices and Intermediates for ADL (p = .44), while both groups displayed on average shorter ADL when

TABLE IV
RESULTS OF THE ANCOVA ANALYSIS FOR THE THREE GROUPS AND THE COVARIATE (BLINKS PER RECORDING).

	Groups	Blinks per recording
%DET	F = 4.06 p = .02* np^2 = 0.10	F = 3.45 p = .07 np^2 = 0.04
%LAM	F = 3.62 p = .03* np^2 = 0.09	F = 7.86 p = .006** np^2 = 0.09
ADL	F = 4.39 p = .02* np^2 = 0.10	F = 0.36 p = .55 np^2 = 0.004
TT	F = 4.28 p = .02* np^2 = 0.10	F = 1.14 p = .29 np^2 = 0.02

Statistical Significance Levels: * $p < .05$, ** $p < .01$

compared to Experts (Intermediates vs Experts: p = .03; while Novices vs Experts: p = .02). Finally, Experts showed shorter TT compared to their less experienced counterparts (Novices: p = .03; Intermediates: p = .02) while no difference was found between Novices and Intermediates (p = .49).

B. RQA Measures and Keystrokes

To further investigate the relationship between behaviors in the game and the keys pressed, we looked into a correlation between the four measures and the four actions performed in Tetris (Total Keystrokes, Total Rotations, Total Translations, and Total Forced Drops). Table V shows the correlation between the actions performed in the game and the RQA measures.

TABLE V
THE r COEFFICIENTS WITH THEIR RESPECTIVE p-VALUES FOR RQA MEASURES AND ACTIONS PERFORMED IN THE GAME.

	Total Keystrokes	Total Rotations	Total Translations	Total Forced Drops
%DET	r = -0.24 p = .03*	r = -0.50 $p < .001$***	r = -0.21 p = .06	r = -0.15 p = .17
%LAM	r = -0.21 p = .06	r = -0.51 $p < .001$***	r = -0.19 p = .09	r = -0.11 p = .29
ADL	r = -0.24 p = .03*	r = -0.45 $p < .001$***	r = -0.22 p = .05	r = -0.17 p = .14
TT	r = -0.24 p = .03*	r = -0.47 $p < .001$***	r = -0.22 p = .04*	r = -0.16 p = .15

Statistical Significance Levels: * $p < .05$, *** $p < .001$

Besides the correlations between actions performed during the Tetris session and the RQA measures, we also looked into differences in actions performed between the three groups. The three groups differed in the average number of keystrokes (F(2,77)= 20.63, $p < .001$, np^2 = 0.35). Experts (M = 2258.05, SD = 687.95) used more keys in the game than Novices (M = 1137.11, SD = 383.91, $p < .001$) and Intermediates (M = 1521.82, SD = 577.63, $p < .001$) across the session. At the same time, Intermediates used more keystrokes than Novices ($p < .01$). We also found that there were statistically significant results when looking at the number of rotations performed across the game (F(2,77)= 3.52, $p < .05$, np^2 = 0.08). However, after applying a post hoc correction, we found that the difference was statistically different between Novices (M = 263.73, SD = 70.66) and Experts (M = 338.05, SD = 97.83; $p < 0.5$) but not between Intermediates (M = 300.42, SD = 93.82) and Novices (p = .17) and between Intermediates and Experts (p = .17). For what concerns the Total Forced Drops and the Total Translations, both the results were statistically significant with F(2,77)= 19.39, $p < .001$, np^2 = 0.33 and F(2,77)= 12.90, $p < .001$, np^2 = 0.25. Concerning the Total Forced Drops, Experts (M = 996.30, SD = 527.15) performed significantly more of them than Novices (M = 261.23, SD = 262.41; $p < .001$) and Intermediates (M = 504.97, SD = 348.53; $p < .01$), while Intermediates performed more than Novices ($p < .001$). Similar results were found when looking at the Total Translations where Novices (M = 612.36, SD = 147.25) performed fewer translations than Experts (M = 716.45, SD = 189.62; $p < .001$) but not than Intermediates (M = 923.70, SD = 225.54; p = .06), and Intermediates performed fewer Translations than Experts ($p < .01$).

C. RQA Measures and Lines Cleared

Finally, we investigated the correlation between the cleared lines and the RQA measures used in this study (see Table V).

TABLE VI
THE r COEFFICIENTS WITH THEIR RESPECTIVE p- VALUES OBTAINED FOR THE NUMBER OF LINES CLEARED AND THE RQA MEASURES.

	Lines Cleared
%DET	r = -0.38 $p < .001$***
%LAM	r = -0.37 $p < .001$***
ADL	r = -0.33 $p < .01$**
TT	r = -0.35 $p < .01$**

Statistical Significance Levels: ** $p < .01$, *** $p < .001$

The results showed a significant correlation across all the RQA measures when looking at the lines cleared. Significant results were found when looking at the number of lines cleared across the three groups (F(2,77)= 65.25, $p < .001$, np^2 = 0.63) Furthermore, Experts (M = 76.65, SD = 17.71) cleared significantly more lines than Novices (M = 23.27, SD = 12.37) and Intermediates (M = 39.66, SD = 15.34). A post hoc comparison revealed that Novices cleared significantly fewer lines than Experts ($p < .001$) and Intermediates ($p < .001$), and that Intermediates cleared fewer lines than Experts ($p < .001$).

V. DISCUSSION

In this work, we tried to answer the following research question: *To what extent can RQA-based measures extracted from the EAR signal be used to identify players with different levels of expertise in Tetris?* What we presented in this work was the first attempt to apply RQA to data extracted non-invasively from a signal containing eyelid movements and blinks. The chosen RQA measures (%DET, %LAM, ADL, and TT) were extracted from the EAR signal, which was used in past studies to extract blinks and other blink-related information. Our results showed differences between the three groups with a different level of expertise in Tetris based on performance obtained during a 13-minute gameplay (average score, number of matches played) and their previous self-assessed experience with Tetris. More specifically, in our study, Expert players conveyed higher levels of complexity across all the measures extracted. This result suggests better adaptability to the task of experts than their less experienced counterparts. Interestingly, our results converge with what was found in other studies using eye-tracking data and RQA to investigate expertise [16], [17]. In these previous studies, expertise and differences between Experts and Novices were investigated in the field of radiology and dermatology. Experts displayed more complex patterns and less predictable behaviors in their eye-gaze. Similarly, in our study, Expert players showed a lower %DET, which means that overall, they had less deterministic and more complex patterns in their eyelid movements compared to their less-experienced counterparts.

For what concerns the %LAM, the results suggest that Experts' eyelid movements had a higher variety in states over time. Blinks per recording, used as a covariate, were a significant predictor in our ANCOVA analysis of the %LAM. This may be explained by the fact that blinks themselves are repeated states in the signal; probably, RQA captures these specific events occurring in the EAR signal as well. However, despite the significant effect of this covariate, we could still find differences between the 3 groups in the %LAM measure. When looking at the ADL, Novices and Intermediates showed longer diagonal lines compared to Experts, which means that they require more time to transition from one state to another, as suggested in other studies [44]. The time required for transitioning from one state to another may be impacting their performance and the final outcome obtained in the game. Finally, the TT, referring to the time the signal remains in a specific phase, displayed shorter vertical lines for the Experts, suggesting a lower period spent in a specific state. By looking at the ADL and TT, we can conclude that Expert participants shift quicker from one state to another and that they linger less in a specific state. We also note from our results that the measures chosen show a direct correlation with the actions the players performed in the game.

Most of the measures chosen display a significant inverse correlation with the number of keystrokes used to play the game, showing that higher complexity is associated with more performed actions. This may be justified by the capability of Experts to be more able to respond quickly and appropriately to the challenges presented in the game. Furthermore, we found a significant moderate inverse correlation between the total number of rotations performed in the games, the number of lines cleared throughout the game session, and the RQA measures. Based on previous studies, we know that stacking and rotating objects is associated with saccadic movements [45]. Something similar may occur in Tetris players when players have to stack and rotate zoids. Following this line of reasoning, we suggest that the RQA measures may be capturing eye-related events such as saccades and pursuits. In either case, an interesting point of our study is that it proves a direct connection between events that occur in the game session and the RQA measures employed in this study. Future research may apply the methodology used in this study to investigate expertise in other video games. Furthermore, this methodology may also be effective in studying phenomena in other fields, extracting RQA measures from the EAR.

Given the relevant connections between blinks and phenomena such as drowsiness [46], fatigue [47], and Parkinson's disease [48], this study may also be of interest to researchers working in other fields. RQA has already been used successfully in other fields when applied to ECG [14], EEG [12], PPG [11] signals, and eye-tracking signal [16], [17]. Something similar may occur with EAR, as it is a signal that can be easily collected using a simple computer webcam. Such studies may also prove that the EAR signal contains more information than that related to blinks alone. Therefore, future research could focus on applying RQA to EAR signals in other fields to further explore other phenomena.

Despite the positive results, it is important to mention the limitations of this study. Firstly, we applied RQA only to one game, and different results may be obtained when investigating expertise in other games. Second, RQA is a computationally expensive method that requires all the time series under analysis to have the same length, since the length of the time series may impact some of the RQA measures [35]. Nevertheless, our work, given the promising results, provides solid background and evidence for the use of RQA combined with the EAR not only in the games domain but also in fields beyond this.

To summarize, our results show that players with different levels of expertise on Tetris convey differences in RQA measures extracted from the EAR. Furthermore, such measures extracted not only can be used to identify experts, but they are also directly correlated with events occurring in the games independently from the levels of expertise defined in this study. Future studies may apply the methods suggested here to other games and other fields to explore the potential of using RQA measures extracted from the EAR to investigate other phenomena.

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