



HAL
open science

Finding Flow in Training Activities by Exploring Single-Agent Arcade Game Information Dynamics

Yuexian Gao, Naying Gao, Mohd Khalid, Hiroyuki Iida

► **To cite this version:**

Yuexian Gao, Naying Gao, Mohd Khalid, Hiroyuki Iida. Finding Flow in Training Activities by Exploring Single-Agent Arcade Game Information Dynamics. 19th International Conference on Entertainment Computing (ICEC), Nov 2020, Xi'an, China. pp.126-133, 10.1007/978-3-030-65736-9_11. hal-03686013

HAL Id: hal-03686013

<https://inria.hal.science/hal-03686013>

Submitted on 2 Jun 2022

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution 4.0 International License

Finding flow in training activities by exploring single-agent arcade game information dynamics

Yuxian Gao^{1,3}[0000-0001-8412-9837], Naying Gao¹[0000-0002-1795-6661], Mohd Nor Akmal Khalid^{1,2}[0000-0002-7909-8869], and Hiroyuki Iida^{1,2}[0000-0001-8412-9837]

¹ School of Information Science, Japan Advanced Institute of Science and Technology, Nomi, 923-1211 Ishikawa, Japan

² Research Center for Entertainment Science, Japan Advanced Institute of Science and Technology, Nomi, 923-1211 Ishikawa, Japan

³ Hebei University of Engineering, Handan, 056001, China
{gaoyuxian,gaonaying1,akmal,iida}@jaist.ac.jp

Abstract. This paper incorporates discussion about game refinement theory and the flow model to analyze simulation data collected from two types of arcade games. A mathematical model of the arcade game processes is formulated. The essence of the arcade games is verified through the game-playing processes of players. In particular, challenge setup could contribute to the addictiveness when the mode is close to flow channel. Risk frequency ratio is applied to measure the process and verified the more entertaining mode of training activities.

Keywords: Arcade games · Game refinement theory · Risk frequency ratio · Flow

1 Introduction

Arcade games firstly referred to entertainment machines installed in public businesses such as restaurants, bars, and amusement centers. Since Apple company launched the arcade games project in 2019⁴, arcade games have entered the limelight with a new look. The term “arcade game” nowadays refers to action video games that designed to play similarly as an traditional arcade game in the game center, with frantic and addictive game-play. It focuses on the user’s reflexes, while usually feature very little puzzle-solving, complex thinking, or strategy skills⁵. Csikszentmihalyi introduces a mechanism to get into the flow which refers to a state of deep enjoyment as an approach to a better life. Playing games is a process of eliminating the uncertainty of game outcome, which is regarded as a typical flow activity [2].

⁴ <https://www.apple.com/newsroom/2019/09/apple-arcade-invites-you-to-play-something-extraordinary/>

⁵ Arcade Game, http://en.wikipedia.org/wiki/Arcade_game

The measure of game refinement (GR) had been used for evaluating sophistication of various games [5]. This study aiming to analyzed game process model identifying players' addiction to the arcade games and similar functional activities. By applying the GR measure, this study is interested in finding the core constitution of an enduring training process.

2 Related Works

A great game “takes one minute to learn but a lifetime to master” [7]. Arcade games perfectly illustrate this feature. “Pong” is the first to appear successfully in the commercial market of the public in 1972 and lead the arcade game gradually into industrialization. Over the decades, although arcade games have been greatly improved in both form and content, their core feature is still as “simple but fun to play”.

Some researchers focus on specific arcade games as objects to re-design the games, test advanced algorithms, or find solutions for human activities. Schrittwieser *et al.* proposed MuZero by introducing an approach combining both high-performance planning and model-free reinforcement learning methods [9]. The MuZero does not require any knowledge of game rules or environment dynamics, tested on 57 Atari arcade games and achieved “a new state of the art”. Cook *et al.* demonstrated the approach to generate complete arcade games by ANGELINA system, scratched by combining rulesets, maps, and object layouts that has designed itself [1]. More recently, studies began to explore the practicalities of using games for learning. Rohlfshagen *et al.* summarized the peer-reviewed research from sociology, psychology, brain-computer interfaces, biology and animals, education, which focused on either game with particular emphasis on the field of computational intelligence [8]. They believed the potential usefulness of arcade games like Pac-Man for higher education is promising.

In essence, arcade game studies mainly focuses on aspects such as (1) using arcade games to assist psychological experiments, (2) improving the efficiency of algorithms, and (3) using arcade games for learning. Nevertheless, research discussing the essence of arcade games from the dynamic of the game perspective is limited to discover optimal flow experience in game-playing processes.

3 Assessment methodology

3.1 Game refinement theory

Game refinement (GR) theory [6] is used to measure the sophistication (i.e., the balance between luck and skill) of a game. It provides an innovative game dynamics view by evaluating the process of a game, simulating the game outcome's uncertainty as a kind of force in mind, which is corresponding to force in nature based on Newton's second law [10].

From the perspective of players, information of the game outcome is a function of time t (in board games would be the number of possible moves). By

considering the process of game as a process of solving uncertainty of game outcome (or obtained certainty) $x'(t)$, (1) is obtained.

$$x'(t) = \frac{n}{t}x(t) \quad (1)$$

The parameter n ($1 \leq n \in N$) is the number of possible options and $x(0) = 0$ and $x(T) = 1$. Here $x(T)$ stands for normalized amount of solved uncertainty. Note that $0 \leq t \leq T, 0 \leq x(t) \leq 1$. The above equation implies that the rate of increase in the solved information $x'(t)$ is proportional to $x(t)$ and inverse proportional to $x(t)$ and inverse proportional to t . Then, (2) is obtained by solving (1).

$$x(t) = \left(\frac{t}{T}\right)^n \quad (2)$$

In most of the board and continuous movement video games, total length of the game is significantly different for players with different levels. For example, Tetris, there will be no end for the perfect player theoretically. We assume that the solved information $x(t)$ is twice derivable at $t \in [0, T]$. The second derivative here indicates the accelerated velocity of the solved uncertainty along with the game progress. After the second derivative, the measure of GR can be formulated in its root square form, where $GR = \frac{\sqrt{n(n-1)}}{T}$, as shown by (3).

$$GR_{classical}^2 = \frac{n(n-1)}{T^n} t^{n-2} \Big|_{t=T} = \frac{n(n-1)}{T^2} \quad (3)$$

It has been found that sophisticated games have a similar value of game refinement located at the zone $GR \in [0.07, 0.08]$ [11, 4, 12]. Another term $n(n-1)$ correspond to the game progress patterns such as one-side game and seesaw game, or the difficulty of completing the task.

3.2 Game refinement measure for target games

Acceleration in mind for arcade games For arcade games those aim playing as long as players can, the measure of game refinement should be reviewed from a more general and macroscopic perspective, the speed of uncertainty being solved is uniformly accelerated. Thus, total uncertainty of game outcome $x(t) = vt$. Consequently, the speed of a game playing, denoted as v , could be counted as the successful ratio to choose the best choice approaching to the end of the game process, namely $v = \frac{1}{T}$. Therefore, risk frequency ratio is defined as $m = 1 - v = \frac{T-1}{T}$. Note that m is dynamic since the player would often feel risky when their skill is weak during the process, and as the players get more skills by practicing, m would decrease.

Gamified experience in single-agent arcade games could be taken as the addiction level of the game. Hence, m could be regarded as the predictor variable of the game challenge. We assume m is the difficulty to move the game forward. Supposing the game ends at $t = T$, solve that $x(T) = vT = \frac{1}{2}aT^2$, we could get

acceleration in mind, namely a -value for single arcade games in this study, as (4).

$$a = \frac{2v}{T} \quad (4)$$

Flappy Bird Flappy bird was released in 2013 developed by Vietnamese video game artist Dong Nguyen. It had been the most downloaded mobile in the app store for IOS, with a download amount of 50 million per month, during which the developer earned 50,000 dollars a day from the in-app advertisements. Process of Flappy birds is uniformly related to learning something or training to acquire some skill. In our simulated Flappy bird game, the player gains a score every time crossing through a pipe is successful. The total game length T is the total number of counted tries, i.e., the number of pipes, thus the successful tries always be one less than the total number. Hence the success ratio v here would be $\frac{\text{Passed Pipes}}{\text{Total Tries}}$. Hence, the a -value of Flappy bird is calculated as (5).

$$a_{\text{FlappyBird}} = \frac{2 * \text{Successful Ratio}}{\text{Total Tries}} \quad (5)$$

Brick Car Racing The game Brick Car Racing is a dedicated handheld game console popular in the early 1990s ⁶. A simplistic racing game in which the player switches between left and right lanes to avoid other cars passing through. The player loses if the car hits one of them. The higher the level, the game's speed will be faster.

In our simulation of the game, the player gains score whenever the car successfully avoids a collision. Therefore, the total game length of this game is the total times that the player needs to slide, which is the number of an encounter of the opposing cars. Unlike the Flappy bird, for every specific number of passes, the game would level up, and the difficulty would increase by increasing the car speed. As the speed suddenly changes, a sudden sense of weightlessness is expected by the players. Hence, the wining speed (v) should be decreasing. From the perspective of risk frequency ratio (m), the player experience towards sudden level changes (speed) is considered. For the Brick Car Racing, risky frequency ratio is measured from level to level. For instance, if there are 100 people participate the level 1, 70% of them passed where the m at level 1 is 30%. Among the 70 people, 35 (50%) of them passed level 2. Then, m at level 2 is 50%, and not 65% since the calculation is not included in the previous stages (30% percent of the players excluded from the latter risk). Hence, referring to the formulation in Section 3.1, the a -value measure of the Brick Car Racing is given as (6).

$$a_{\text{BrickCarRacing}} = \frac{2 * \text{Level based Success Speed}}{\text{Passed Car At The Level}} \quad (6)$$

⁶ https://retroconsoles.fandom.com/wiki/Brick_Game

3.3 Flow Theory and force in mind

Flow, originally derived from Csikszentmihalyi’s observations of artists, chess players, climbers, and composers. He observed that when these people were engaged in their work with almost total concentration, often losing track of time and awareness of their surroundings [3]. They engaged in their individual activities out of a common sense of fun. These pleasures are derived from the process of activity, and the external rewards are minimal or non-existent. This flow experience caused by concentration is considered to be the best experience usually happening when skill people acquired and challenge they faced at a comparable level. The formula is shown as $Flow = \frac{Skill}{Challenge}$ (the goal is 1.0).

From the view of game informatics, with the decreasing of m , people would feel boring since the game is with no longer has much uncertainty for the player as at the beginning. They would come to the phase corresponding to the boredom zone in flow theory when an event needs high skill but with low challenge.

In nature physics, force is any interaction that will change the motion of an object when unopposed. Force can cause an object with mass to change its velocity (which includes to begin moving from a state of rest), i.e., to accelerate. Therefore,

$$F = ma = \frac{2mv}{T} \quad (7)$$

As discussed in Section 3.1, the acceleration in mind could be the measure about ratio of skill and challenge. In order to maintain the movement of game or activity, force should not be decreased, therefore, force in mind could be the measure of flow state. The bigger the force in mind is, the higher possibility the game could be in the flow longer.

4 Data and analysis and discussion

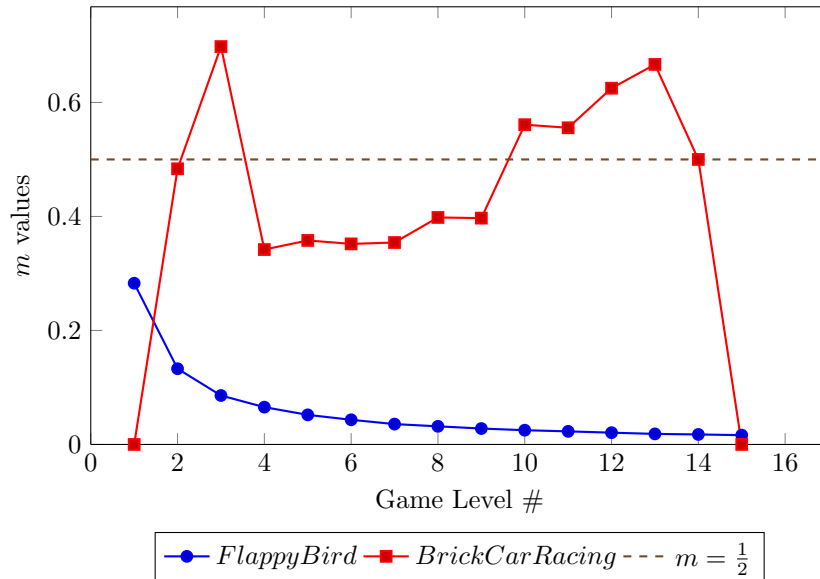
The essence of game attraction is uncertainty [5]. From the information perspective we could also agree that $n = 2$ is the most competitive case when the win rate and lose rate are equals, i.e. where the game outcome entropy⁷ reaches the highest value. In this study, two arcade games were considered for data collection. The open-source code is adopted and simulation is conducted by using PyGame. The Flappy bird, whose challenge setup is constant, as well as the Brick Car Racing with increasing difficulty. Although the interface and presenting form of the two games are different, the core playing model is similar, which is moving the character to avoid collision on obstacles to play as long as possible. The two classic games could represent for many popular arcade games recently such as Temple Run(as well as other Run games), Shooty Skies, Jump Jump. The Flappy bird and Brick Car Racing games represent two typical basic single-agent arcade games. One represents for those with constant difficulty while the other for those with changing difficulty.

⁷ $H(X) = -\sum_i P(x_i) \log_b P(x_i)$, information entropy by C.E., Shannon.

Table 1. The measure of game refinement of target arcade games

Game	v	m	n	T	a	F
Flappy Bird	0.9414	0.0586	1.0689	32	0.059	0.00345
Brick Car Racing	0.5506	0.4494	1.8161	20	0.055	0.02474

After all the data has been aggregated, the game refinement value of target games is shown in Table 1. Data shows that the measure of game refinement are similar for the two games, both of which are lower than the most refined GR zone. Previous work on serious games reveals that activities that happened in a serious environment would not be as entertaining or relaxing as fun games. In such a situation, game elements are used to increase motivation and engagement of the learning process so that the GR value will be much lower [5]. Flappy Bird has *a-value* of 0.059, and Brick Car Racing is 0.055, both locate between fun game and serious game. However, the force in mind is differs significantly. The bigger force of Brick Car Racing implies the game is has more flow force, which can maintain a longer period of flow state.

**Fig. 1.** *m* value change with level increase in Flappy Bird and Brick Car

With difficulty increased, the expected risk of the player is (kind of) reset. When the players gradually relax their vigilance and become more comfortable, the game suddenly accelerates, and then the players become excited again. This situation is validated by the depiction of the game process of the Brick Car Rac-

ing that changes dynamically (m value in Figure 1). As the process repeats, the player experiences weightlessness similar to that of a roller coaster, keeping them always curious about the outcome; thus, the player would get highly attracted.

The activities with skill changing perform as the trend as a blue line in Figure 1 are training activities, which mostly driven by an inner sense of accomplishment. More often than not, it is a steady, repetitive process. While activities with trend given as red in Figure 1, skill increase defines the training activities as entertaining. As the game difficulty increasing, player skill gets better; and as player skill improves, the challenge gets harder, and so on. This kind of activity stems from people’s instinctive curiosity about the unknown and is an implicit kind of entertainment. Thus, the relationships between boring training and gamified training are established.

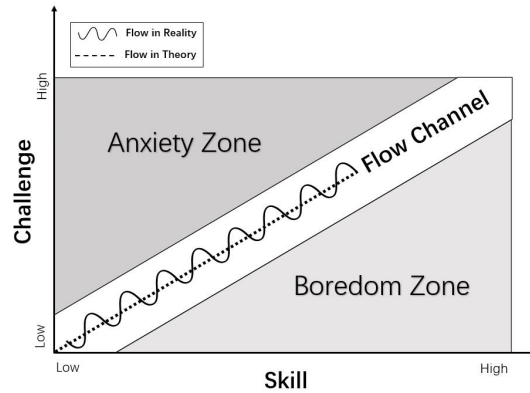


Fig. 2. Flow in theory and in practice

The difficulty that suits the player’s skill level needs to be dynamically changed to keep the player engagement stays within the flow zone. The process of keep playing single-agent arcade games is boring training. The more attempts the player has, the more skillful they will be. As they become skillful, they are less likely to play the game or do the training. If the game difficulty is adjusted, the training process can become more exciting and long-lasting. The result showed in the Figure 1 could be aligned with the flow model in theory and in practice as shown in the Figure 2.

The game process of the arcade game is metaphorically a continuous training process. The fluctuation of GR in Figure 1 indicates an information process similar to ride a roller coaster, which can keep the player stay in the “challenge equivalent to skill” state, as shown in Figure 1. Therefore, the regulation of single-agent arcade games would be the benchmark for us to understand the training process and to overcome the persistence at the later phase of skill training.

5 Conclusion

This study uses two typical single-agent arcade games as a benchmark to study the arcade game's essence where game refinement measure were applied and data were collected and analyzed. Flow experience in theory and real cases were described where a logical model of the arcade game process was formulated. Result shows when the risk frequency ratio changes irregularly and repetitively, the process is more likely to be in the flow state in reality. The difficulty increases with the level case is closer to flow and was verified by the measure of game refinement. It offers us inspiration if we need to turn a training event engaging and long-lasting; the game difficulty needs to be adjusted dynamically based on the player's increase in skill. This finding will contribute to serious game design to help people learning things persistently.

References

1. Cook, M., Colton, S.: Multi-faceted evolution of simple arcade games. In: 2011 IEEE Conference on Computational Intelligence and Games (CIG'11). pp. 289–296. IEEE (2011)
2. Csikszentmihalyi, M.: *Beyond boredom and anxiety* (1975)
3. Csikszentmihalyi, M.: Toward a psychology of optimal experience. In: *Flow and the foundations of positive psychology*, pp. 209–226. Springer (2014)
4. Gao, Y., Li, W., Xiao, Y., Khalid, M.N.A., Iida, H.: Nature of attractive multiplayer games: Case study on china's most popular card game—doudizhu. *Information* **11**(3), 141 (2020)
5. Iida, H.: Serious games discover game refinement measure. In: 2017 International Conference on Electrical Engineering and Computer Science (ICECOS). pp. 1–6. IEEE (2017)
6. Iida, H., Takahara, K., Nagashima, J., Kajihara, Y., Hashimoto, T.: An application of game-refinement theory to mah jong. *Proceedings of Icec Ndhoven* **3166**, 333–338 (2004)
7. Kunkel, B.: *How alex pajitnov was tetris-ized! why tetris' creator got the cultural bends upon his arrival in america*. Good Deal Games (2003)
8. Rohlfshagen, P., Liu, J., Perez-Liebana, D., Lucas, S.M.: Pac-man conquers academia: Two decades of research using a classic arcade game. *IEEE Transactions on Games* **10**(3), 233–256 (2017)
9. Schrittwieser, J., Antonoglou, I., Hubert, T., Simonyan, K., Sifre, L., Schmitt, S., Guez, A., Lockhart, E., Hassabis, D., Graepel, T., et al.: Mastering atari, go, chess and shogi by planning with a learned model. arXiv preprint arXiv:1911.08265 (2019)
10. Sutiono, A.P., Purwarianti, A., Iida, H.: *A Mathematical Model of Game Refinement*. (2014)
11. Sutiono, A.P., Ramadan, R., Jarukasetporn, P., Takeuchi, J., Purwarianti, A., Iida, H.: *A mathematical model of game refinement and its applications to sports games* (2015)
12. Xiong, S., Zuo, L., Iida, H.: Possible interpretations for game refinement measure. In: *International Conference on Entertainment Computing*. pp. 322–334. Springer (2017)