Designing Human-Computer Multi-agent Collaboration in Productive Multi-Player Games

(Short Paper)

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ABSTRACT

This research explores *productive multi-player games* as a platform for human-computer agent collaboration. A multiagent perspective is taken to examine the principles of both gameplay and mechanism design for productive games. To engage human players in sustained gameplay, the game agents are designed with the *flow* and *dramatic* principles. To ensure productivity, the game mechanism is designed such that rational agents, both human and software, will follow the target strategy to reach subgame perfect equilibrium. The design principles are demonstrated and evaluated using PhotoSlap, a multi-player productive game for photo annotation.

Categories and Subject Descriptors

I.2.11 [**Distributed Artificial Intelligence**]: Multiagent systems

General Terms

Design, Game

Keywords

Productive game, gameplay, strategy analysis, agent collaboration

1. INTRODUCTION

Tasks that are natural for humans can be extremely difficult for computers. For example, humans do remarkably well in identifying faces, even under various degradations [8]. On the other hand, computers often outperform people on tasks that are tedious, boring and time-consuming. *Human computation* can be shown to turn games into productivity tools [9].

In this research, we explore productive multi-player game as a platform for collaboration among software agents and human players. Software agents are defined for productivity, gameplay control, and coordination. In addition to automated players who try to get high scores against human players, the game agents adjust the level and pace of challenges in order to keep players engaged in the game. Taking a game-theoretic approach, the game mechanism coordinates both human and computer players to maximize their payoffs.

This paper presents the design principles of both gameplay and game mechanism from a multiagent perspective. To engage human players in sustained gameplay, the game agents are designed with the *flow* and *dramatic* principles. To ensure productivity, the game mechanism is designed such that rational agents, both human and computer, will follow the target strategy to reach subgame perfect equilibrium. A multi-player productive game, PhotoSlap[1], is used to demonstrate human-computer collaboration on the task of photo annotation. The design of Photoslap is evaluated in terms of productivity and game experience in a small-scale user study.

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2. RELATED WORK

Games can be powerful tools for enabling human-computer collaboration on complex tasks. For example, von Ahn first demonstrated the power of *human computation* using the simple yet interesting ESP Game [9]. Users are motivated to contribute their image labeling skills, thereby turning the tedious manual labeling process into entertainment. Google Image Labeler[2] has licensed this method to help improve the quality of image search. Another productive game, Peekaboom, was proposed to exploit people's natural ability to locate objects in images [10].

Good games are fun and engaging by offering a variety of challenges[3], satisfaction, and rewards. Rollings and Adams [7] defined *gameplay* as "one or more causally linked series of challenges in a simulated environment." Gameplay design is a process that connects a series of challenges to fun activities. To keep players engaged, games must adapt to the growing abilities of the player [2].

A mechanism defines the "rules of a game" [6]. In game theory [5], *mechanism design* specifies the rule of interaction in order to yield the desired outcome in a multi-agent environment.

3. PRODUCTIVE GAME DESIGN

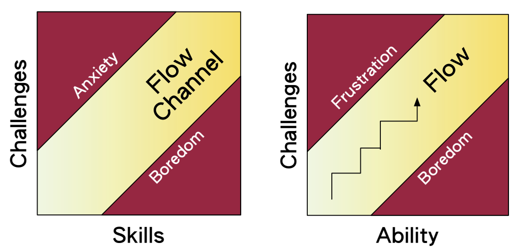
[1]http://photoslap.csie.org
[2]http://images.google.com/imagelabeler/
[3]http://www.gamasutra.com/features/20011012/garneau_01.htm

Productive games produce purposeful information as a result of the actions taken by the human players. The design process involves two components presented below.

3.1 Gameplay Design

Gameplay, which connects a series of challenges to fun activities, is the core element of any productive game. People are motivated to spend time playing games for pleasure.

The theory of *flow*, proposed by psychologist Mihaly Csikszentmihalyi, defines flow to be a balanced state in the central region between challenges and player skills [1]. Figure 1(a) shows the flow state as a channel between *anxiety* due to overly difficult challenges and *boredom* due to overly simple challenges in a game.



(a) The flow state (b) Ideal path of gameplay

Figure 1: The state of *flow* in gameplay.

For a player to be fully immersed in the game activities, the difficulty of challenges should grow with the ability of the player. Figure 1(b) shows the path balanced carefully between frustration and boredom that game designers strive to achieve [2]. The game agent dynamically adjusts the balance between the difficulty of the challenges against the player's ability. The *flow principle* is defined to create a deep and persistent player engagement.

DEFINITION 1. **Flow Principle**
Given the ability of a player π and his/her flow region $\pm\sigma$, he/she can be ensured to stay in the flow state by adjusting the difficulty of challenges ω such that $\pi - \sigma \leq \omega \leq \pi + \sigma$.

The pace of experiencing challenges in a game is important as well. From the perspective of productivity, more challenges bring more products. However, continuous and monotonous challenging pattern may exhaust players with boredom.

A good game is like an absorbing drama that people fully enjoy. Each stage in a game is analogous to an act in a drama. To avoid monotonous stages, a good game should produce tension for the players following the dramatic arc in figure 2, modulated by periodic rising and falling [2].

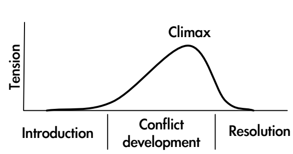


Figure 2: The dramatic arc

Let p be the probability of presenting a challenge in a game. We can define the dramatic principle as follows.

DEFINITION 2. **Dramatic Principle**
Challenges in a game are presented according to the probability $p = N \cdot e^{\Delta t \cdot (K_i + K_g \cdot t)}$, where N is a normalizing constant, Δt is the duration since the last challenge, K_i is a constant for adjusting the initial tension, K_g is a constant of the growing speed of tension, and t is the current time.

The probability p grows with time, but is reset whenever a challenge is presented.

3.2 Mechanism Design

Given that there can be both human players and software agents in a multiagent productive game, the game mechanism should be designed to satisfy their different goals. Human players play the game for fun and the accumulation of scores. The software agents play the game to engage the human players in sustained gameplay for maximizing productivity. As a result, players in the agent subgame have different target strategies and payoffs from players in the human subgame.

Human Subgame.

Humans play the explicit side of the game. The target strategies of humans aim to obtain the most rewards, for example, the highest score or the instant visual feedbacks, from the game. The payoffs for human subgames are usually different from the target information harvested from the productive game.

In the design phase, a game-theoretic approach is taken to separate each human player into his own subgame with strategy profiles according to the game rules. Each expected payoff of strategies was then calculated based on the probabilities obtained by analyzing the extended game. The behavior of each player is predicted to identify the Nash equilibria, which leads to subgame perfect equilibrium of the entire game.

Agent Subgame.

Agents play the implicit side of the game. The relationship between human players and computer agents could be competitive or cooperative. All the computer agents were toward the same goal, which was to maximize the productivity. The bot agent player should act like a rational human player with a similar strategy, except that they have better access to hidden information or human player stats. Given that the bot agents are programmed by the game designer, they will always follow the desired strategies.

4. CASE STUDY: PHOTOSLAP

PhotoSlap, introduced in [4], is a multi-player online game with the rules similar to the popular card game *Snap*.

Players take turns in flipping the cards containing face photos. Each player decides whether to slap the last two cards based on whether the photos are deemed to be the same person. Upon starting a new game, each player enters the *trap* stage to define matching pairs to serve as the ground truths. After setting the traps, players move on to the *game* stage, during which three possible actions, *Flip*, *Slap*, and *Object*, may be performed.

4.1 Gameplay

In PhotoSlap, the core challenge is to recognize the faces attached on cards and to be the fastest one who reacts to slap on the cards. The challenge can be defined as trying to be the fastest one among competitors; the ability of a player can be defined as his/her *reaction* (including recognition and slapping) time. A player may feel frustrated if the player's reaction time is much slower than that of the competitors. On the other hand, a player may be bored if his reaction time is much faster than that of the competitors.

Following the flow principle, the game agent collects statistics on the reaction time of players and match them up with human or robot players with comparable abilities.

Following the dramatic principle, the pace of experiencing challenges is the tempo of the appearance of a matching pair. Each time a card is flipped, PhotoSlap makes a decision about whether to present a challenge based on the probability $p = N \cdot e^{\Delta t \cdot (K_i + K_g \cdot t)}$ as previously defined. The rate of matching pairs is low at the beginning, and grows exponentially as the game proceeds.

4.2 Strategy Analysis

We perform game theoretic analysis to show that rational players do take the actions prescribed by the target strategy in PhotoSlap. For example, players tend to set a trap and to slap when they believe the two photos do match, i.e. images of the same person. PhotoSlap is modeled as a multi-player extensive game with *imperfect information* as shown in Figure 3. Player 1 is the player who sets the trap. Player 2 is the player who slaps first and player 2 is said to stay if no player slaps. Player 3 is the player who objects first, and player 3 is said to stay if no player objects.

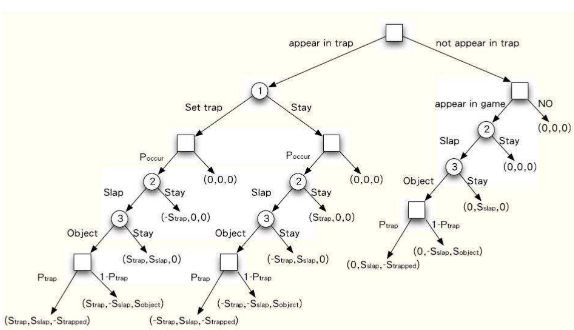


Figure 3: Game tree for each photo pair.

The target strategy can be shown to reach subgame perfect equilibrium in all subgames by examining all possible strategy profiles s_i as shown in Table 1 below.

	Player 1	*Player 2*	*Player 3*
s_1	Set trap	Slap	Object
s_2	Set trap	Slap	Stay
s_3	Set trap	Stay	Object
s_4	Set trap	Stay	Stay
s_5	Stay	Slap	Object
s_6	Stay	Slap	Stay
s_7	Stay	Stay	Object
s_8	Stay	Stay	Stay

Table 1: All possible strategy profiles.

CLAIM 1. *Given the subgame in which player 3 is the root, player 3 would object if he/she believes player 1 would stay; stay if he/she believes player 1 would set trap.*

CLAIM 2. *Given the subgame in which player 2 is the root, player 2 would stay if he/she believes player 3 would object; slap if he/she believes player 3 would stay.*

CLAIM 3. *Given the subgame in which player 1 is the root, player 1 would set the trap if he/she believes player 2 would slap; stay if he/she believes player 2 would stay.*

Consequently, s_2 and s_7 are the only strategy profiles satisfying Nash equilibrium in all subgames. The proofs and detailed analysis may be found in [3].

5. EVALUATION

In the post-game questionnaire previously reported in [4], users gave feedbacks on "Is PhotoSlap fun?" and "Will you play the game again?" Photoslap received an average score of 7.6 from a 10-point fun scale. All users claimed that they would like to play the game again.

To measure the effect due to the gameplay design principles, a user study is conducted to evaluate Photoslap. Each group consists of one volunteer and 3 bot players that are designed to "slap" and "object". The volunteer users continuously played PhotoSlap for two 30-minute sessions, which contain two game sets for the evaluation of the flow principle and of the dramatic principle respectively. User feedbacks were collected after the end of each game. The test dataset used in all user experiments contains 572 faces of various poses and illumination from 24 different persons, and all faces were manually labeled and annotated by the authors.

Flow Principle.

In the first 30-minute session of this user study, each player was asked to play PhotoSlap with two different configurations. One configuration groups the players randomly, while the other configuration matched the human player with bot players chosen according to the flow principle. This study measures the percentage of meeting challenges with proper difficulty. In general, higher percentage of proper challenges is a good indicator of the player's desire to keep playing.

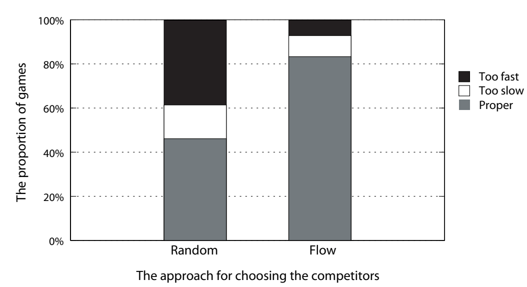


Figure 4: Percentage of proper challenges given random vs. flow principle.

As shown in Figure 4, a player has a 46% chance of meeting challenges of proper difficulty in the random case. In contrast, by adopting the flow principle, the players have an 83% chance of getting proper challenges.

Dramatic Principle.

In the second 30-minute session of this user study, each player was asked to play PhotoSlap with two sets of configurations. The first set of games use a constant probability (10%, 20%, 40%, 50%, 60%, and 80%) of presenting challenges. This study measures user comfort level and satisfaction given the frequency of experiencing challenges. The experimental results are shown in Figure 5.

The results indicated that most players feel comfortable when the chance of getting proper challenges is between 40% and 50%.

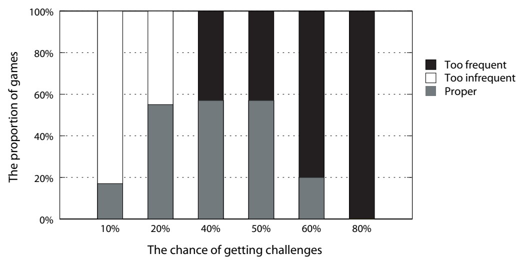


Figure 5: The proportion of proper games with different constant pace of challenges.

For example, when PhotoSlap adopts the 50% configuration, the players have a 57% chance of feeling that the pace of challenges is proper.

The second set of games is designed to measure the effect of the dramatic principle on user satisfaction as well as the ratio of output production, which averaged about 50% out of all presented cards.

Figure 6 shows the experimental results for PhotoSlap using the dramatic principle, with parameters $C = 0.7$, $K_i = 0.27$, and $K_g = 0.25$.

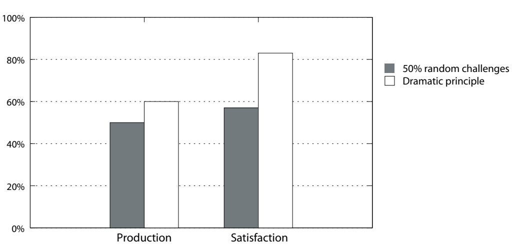


Figure 6: The comparison between using 50% random challenges and using the dramatic principle.

The results demonstrated that the dramatic principle improved the production factor O to 60% and the user satisfaction rate to 83%.

Productivity.

Productive games can serve as a productivity tool to produce useful information. The quality of a productive game is measured by its *productivity*, which can be defined as

$$Productivity = N \cdot T \cdot O \cdot Q$$

In this general measurement, N is the number of players per unit time, T is the involved time of each player, O is the amount of output per unit time, and Q is the qualified proportion of output.

We have conducted small-scale experiments using four focus groups. Each group of four human players played PhotoSlap for a 30-minute session (about 11 games) without break. Links between face photos are built as a result of player actions. The productivity is measured by the number of links established as well as the percentage of the correct links. In the four focus-group studies, there are 1455 correct links out of the 1480 links are formed in 8 person-hours. In other words, each game produce 12.3 links per minute and 98.31% of them are correct.

6. CONCLUSION

This research explores productive multi-player games as a platform for human-computer multi-agent collaboration. We introduced the *flow* and *dramatic* principles for gameplay design, as well as *game-theoretic analysis* of mechanism design for productive multi-player games.

Automated software players are deployed to achieve high scores against human players, while game agents adjust the level and pace of challenges to engage human players for sustained gameplay. For productivity, the game mechanism is designed with a target strategy to ensure subgame perfect equilibrium. That is, any rational player will choose to take the actions prescribed by the target strategy. PhotoSlap, a productive multi-player online game for photo annotation, is used to demonstrate the design principles with experimental evaluation.

This research extends the idea of *human computation* in several aspects. Formulating productive multi-player games as human-computer multi-agent collaboration enables us to address game design in two parts. The proposed design principles provide a disciplined approach to designing productive games for sustained and satisfying gameplay. The game-theoretic strategy analysis provides a foundation to ensure the quality and productivity of the games. The evaluation criteria as defined provide empirical support for fruitful collaboration among human and computer players in a game.

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