Dynamic Difficulty Adjustment via Fast User Adaptation

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Abstract

Problem

- Conventional Dynamic Difficulty Adjustment (DDA) methods require adjusting parameters in the game to generate levels for various players.
- Recent DDA approaches based on deep learning can shorten the time-consuming tuning process, but require sufficient user demo data for adaptation.

Solution

- This paper presents a fast user adaptation method that can adjust game difficulty for various players even with small amounts of demo data by applying meta-learning algorithms.

Background

- DDA has been shown to have positive effects on player immersion and long-term motivation.
- One of the simplest but most powerful ways to implement DDA is to increase or decrease in-game parameters or AI levels according to the player's in-game performance.

  The method of adjusting parameters requires careful tuning and is time consuming.

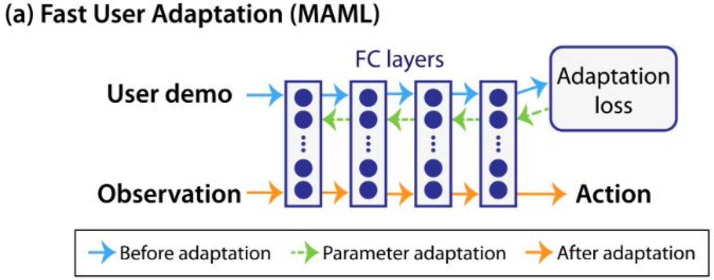
- Some methods adapt game challenges to the player by generating enemy agents using the player's actual movements and strategies.

  The need for a new training for each player would have required an adequate data acquisition process.

- This paper proposes a new DDA approach called fast user adaptation (FUA) based on deep neural networks, which can quickly adapt to players' abilities with little play data.

Method

- The FUA method is to modify the *model-agnostic meta-learning* (MAML) algorithm to train a model that can quickly respond to different users (Figure 1(a)).
- MAML Learning Equation: $$\min_{\theta} \sum_{T} L(\theta - \alpha \nabla_{\theta} L(\theta, D^{T}_{demo}), D^{T}_{valid}),$$
  - θ : Parameters (neural net weights)
  - $L(\theta, D_{demo})$: Loss function using demo data
  - α : Learning rate
  - $\nabla_{\theta} L(\theta, D_{demo})$: Parameter gradients
  - D_{valid} : Validation data (used to evaluate the results of player adaptation)



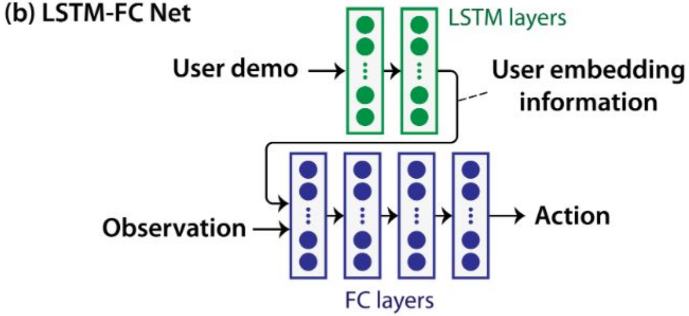


Figure 1. Overview of the DDA network models we implemented. (a) Fast user adaptation. (b) LSTM-FC Net.

Method

$$\min_{\theta} \sum_{T} L(\theta - \alpha \nabla_{\theta} L(\theta, D^{T}_{demo}), D^{T}_{valid}),$$

- Where $L(\theta , D^T)$ denotes the loss value when data D^T, obtained from task T, is fed into the model with parameter θ.
- The FUA method is an application of the MAML algorithm, which instead of using training data from various tasks (D^T), uses data from various players (D^P).
- This DDA method is intended to make an agent quickly learn the player’s movements so that the player faces an agent who plays similarly to himself/herself.

Experiment

- A user test was conducted in which participants were pitted against a DDA-applied agent in a one-on-one virtual ***Air Hockey*** game.
- To validate the FUA model, two additional baseline DDA methods were implemented: another data-driven approach using neural networks (***LSTM-FC***) and a conventional DDA approach.
- When the same data were exploited for five epochs, the FUA model training was about nine times faster than the LSTM-FC Net (2 hours vs 18 hours).

Experiment

- Participants: 9 participants between 22 to 29 years of age.
- Participants took a part in three 4-minute sessions with the three different types of DDA agents in random order.
- The initial difficulty adjustment of each session was performed using data acquired during a pre-session of about one minute performed immediately before each session.

Result

- Evaluate DDA methodology using both objective and subjective evaluation indicators(Figure 2 (a) and (b)).
- Figure 2(a) shows that our method is comparable to the conventional method in both win-loss ratio and puck possession, and is superior to LSTM-FC nets.
- Figure 2(b) shows the subjective evaluation results of our user test. Our DDA method shows superior results to the LSTM-FC Net in terms of the enjoyment, engrossment, and, in particular, the suitable difficulty score.

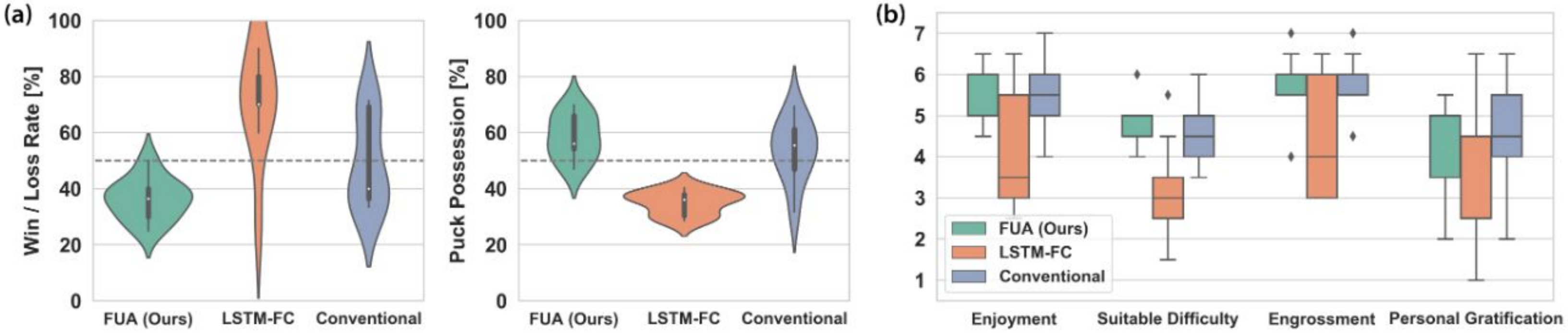


Figure 2. (a) Objective evaluation results and (b) subjective evaluation results of each DDA method.

Conclusion

- This paper proposed a new DDA method: fast user adaptation based on a meta-learning algorithm.
- FUA method surpassed a deep neural network-based baseline in both objective and subjective evaluations, and showed a much faster learning speed.
- In addition, FUA method showed comparable performance to the conventional DDA even though it has the advantage of not requiring time-consuming parameter tuning.

Thank you for listening