MiaoSuan Wargame: A Multi-Mode Integrated Platform for Imperfect Information Game

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***Abstract*—Just like data plays a fundamental role in perceptual intelligence, simulated environments become the cornerstone of artificial agents in cognitive intelligence. Meanwhile, the evaluation of decision agents has put forward an urgent need for human-machine accessible game platforms, on which humans and agents can interact and confront, even the "Turing test" can be conducted. In this work, MiaoSuan wargame platform, a human-computer gaming platform for multi-agent imperfect information game is proposed. It provides multiple scenes and tasks, together with various confrontation forms (computer vs. computer, human vs. computer, and human/computer hybrid) and game modes (online confrontation, offline training, and Turing test) for agents' training and evaluation. The MiaoSuan platform is constructed as a modular architecture with separable engine, AI interface, human interface and other functional modules, in which different game environments and tasks can be conveniently integrated. Two kinds of workflows, online confrontation and offline training, are designed to schedule different modules to achieve their corresponding game modes. Besides, based on this platform, a "Turing test" method for agent evaluation can be implemented automatically. It introduces a comprehensive evaluation of agents' performance through subjective human assessment or objective data analysis, rather than only depending on their game scores. The MiaoSuan wargame platform is widely used in individual practice and organized events. It is available at http://wargame.ia.ac.cn/.**

Keywords—open platform, human-computer gaming, AI evaluation, Turing test, imperfect information game, wargame

I. INTRODUCTION

In recent years, superhuman game algorithms such as AlphaGo [1] and AlphaStar [2] have made significant progress. It is regarded that artificial intelligence (AI) technology is rapidly developing from perceptual intelligence into the stage of cognitive intelligence. In cognitive intelligence, the agents need to "think" (understand situations and make decisions) like humans. Driven by this specific goal, they usually execute the "observation-orientation-decision-action" (O-O-D-A) process [3] repeatedly in complex environments. Compared with perceptual intelligence, there are no standard datasets or answers for training and evaluating agents' performance. Therefore, human-computer gaming is regarded as an internationally recognized method for the evaluation of cognitive intelligence. At this point, an interactive decision-making environment in which both humans and agents can access for confrontation and evaluation is very necessary. There have been several popular platforms for decision agents, such as Open AI Gym[1], PySC2[2] and OpenSpiel [4], committing to provide integrated game environments. But these platforms mainly focus on the development of agent algorithms in some types of games such as StarCraft, video games, and board/card games, with less attention to the all-sided evaluation of agents and the participation of humans in the loop. The wargame is a simulation game for warfare. With the development of information technology, the implementations of wargames as computer simulations become more and more popular. The actions in the wargame contain elegant tactical thoughts, which makes higher requirements on the cognition and decision-making abilities of agents. Meanwhile, the wargame is also more in line with the development trend of cognitive intelligence, with the characteristics of imperfect information, large-scale state- action spaces, asymmetric environments, high randomness, and strategy intransitivity [5]. Therefore, the study of wargames is of great value. And an integrated wargame platform supporting agent development and evaluation and human-computer confrontation will certainly be of great help to its progress.

To this end, we developed and released an integrated wargame platform. Different from the traditional ways which briefly consider wargame as a strategy research environment for a few people, taking wargame as an imperfect information game platform faces many challenges. Its natural complexity brings great challenges to the building of valuable platforms, which is mainly featured in the following aspects: (1) man-in-loop decision. In the wargame, players constantly interact with the game environment. So the update of environmental information and the issuing of action commands need to be timely. (2) multi-player environment. There are multiple factions in the wargame. Each faction can have one or more players. (3) imperfect information. Each player in the game has its own game view. And the game information is shared in the same faction and different among different factions. Such confidential information makes data processing and communication more complex. (4) multiple confrontation scenes. From the major terms, their maps and scales are

[1] https://gym.openai.com

[2] https://github.com/deepmind/pysc2

different. And from the details, their schemes about the configuration of pieces, weapons and landmarks are countless. So the platform needs to support the flexible changes of game scenes. Apart from these, as an open platform, it should support convenient human access and agent deployment. And considering the different identities of players, the game forms it should support can be further related to the cooperation and hostility between humans and agents. Besides, its openness also has high demands of the load and concurrency capabilities.

The MiaoSuan platform, presented in this paper, is an open and integrated imperfect information game platform for the wargame. It provides many wargame environments with different scenes and tasks and supports convenient human access and agent deployment. These provide convenience for the confrontations between humans and agents, whose forms can be human vs. human, computer vs. computer, human vs. computer, or human/computer hybrid. It also provides standard interfaces for the development of agents and various methods for the evaluation of agents. We hope the MiaoSuan platform makes wargame AI research handy and sustainable, and further promotes the research on the complex imperfect information game. The main contributions of this work are as follows:

- We build an integrated imperfect information game platform with an open architecture. There are multiple wargame environments and agents built-in. Researchers can also link their independently developed agents and other human-computer gaming environments to this platform, as long as they conform to the interface standards.
- A complete game platform with multiple confrontation modes is provided, which include online confrontation mode and offline training mode. The former can be further divided into four real-time confrontation forms: human vs. human, computer vs. computer, human vs. computer, and human/computer hybrid. And the latter supports the step-by-step training of agents in the computer vs. computer form.
- A "Turing test" method for the evaluation of decision-making agents is presented, which can be implemented automatically on the MiaoSuan platform based on its confrontation function. It enriches agents' evaluation methods by human Turing questionnaires and replay data analysis, and can provide more comprehensive evaluations of agents' performance.

The following parts are as: Section II describes the related work about open game platforms, wargame platforms, and evaluation methods in artificial intelligence. In Section III, the architecture and the main workflow of the MiaoSuan platform are presented, and a Turing test based agents evaluation method is proposed. In Section IV, we show the applications of this platform. Finally, Section V presents the conclusion and possible future work.

II. Related Work

A. Open Game Research Platforms

Many open game research platforms have already sprung up since cognitive intelligence has been concerned. Examples include platforms with integrated environments such as the Open AI Gym which provides many environments for single-agent decision-making problems, the OpenSpiel and LUDII[3] which mainly focuses on classic board and card games, and the GVGAI [6] which brings many research environments for video games, and also include platforms with specific game environment such as the PySC2 for StarCraft, the ViZDoom[4] for 3D first-person shooter, and the BotBowl[5] for a fantasy football game named Blood Bowl. There are also some platforms for strategy games with a war background, such as the DAIDE[6] and DipGame [7] for a turn-based, perfect information and multi-player board game named Diplomacy. The main goal of the game is to acquire the required number of supply centers throughout the map by actions of holding, moving, and supporting other units. It allows players to negotiate with each other and form or break coalitions, so its agents mainly focus on the negotiation and trust reasoning algorithms [8][9]. Another famous platform for strategy games with a war background is Stratega[7]. It is an integrated platform with many turn-based or real-time game environments such as Kill the king, City Capturing and Settlers. As board games with multiple entities, grid maps (each grid has a geology feature) and random factors, the games in Stratega are similar to the wargame described in this paper. But they are very different, mainly in the essence and complexity of the game. Firstly in terms of game essence, the wargame is a warfare simulation tool, whose rules are based on war experiences. While the games in Stratega are more like smaller-scale fights with a war background. And then in terms of game complexity, the games in Stratega have much simpler map features than the wargame. Although their maps are made up of grids with different terrains such as forest, water and plain, the grids in Stratega only have two binary attributes: "IsWalkable" (whether the grid is walkable) and "BlocksSight" (whether the grid can block the view of units). It's more complicated in the wargame. Each grid has a fixed elevation and different energy costs for different move modes. These diverse attributes make the rules of observation and movement in wargame more complex.

B. Wargame Platforms

Wargame, from the Prussian Kriegsspiel [10], has a long history. As early as the 19th century, it has received great attention. With the development of artificial intelligence technologies, it becomes a typical testbed for imperfect information game research. And there are many researches on wargames, such as data mining [11][12], situation cognition [13][14] and intelligent decision algorithms [15][16]. However, these researches' environments are relatively scattered. There is not yet an integrated and shared wargame platform providing sufficient support for the wargame research.

At present, the wargame platform supporting agent access has just emerged, and the wargame platform supporting the development and evaluation of large-scale agents is almost nonexistent. Although there are some platforms for wargame

[3] https://ludii.games/index.php
[4] http://vizdoom.cs.put.edu.pl
[5] https://github.com/njustesen/botbowl
[6] http://www.daide.org.uk/
[7] https://github.com/GAIGResearch/Stratega

implementations such as MoZi[8] and Armored Assault[9]. They mainly provide human-oriented game environments, and cannot provide sufficient support for the development and understanding of AI algorithms, let alone the evaluation of agents. Besides, they do not open their replay data, which makes them mainly used for experiments and analysis of some specific people.

In addition to these real platforms, some researches have been published to give assumptions to the new generation of wargame system. Si et al. [17] proposed an architecture of the next-generation large-scale computer wargame system which contains foreground application layer, background application layer, core service layer and infrastructure layer. Hu et al. [18] expanded the intelligence of the wargame system from three hierarchies: assistance, control and action. Goodman et al. [19] proposed an envisaged wargame AI framework that includes AI algorithm implementations, core and wargame implementations. Although some researches gave recommendations on the wargame system, they mainly focus on its capability of confrontation. There is no complete idea of wargame AI testing and evaluation based on confrontations.

C. *Evaluation Methods in Artificial Intelligence*

There are three main kinds of evaluation methods in artificial intelligence: problem benchmark, peer confrontation, and human assessment [20]. Problem benchmark usually refers to using standard evaluation procedures to compare different algorithms under specific test scenarios. Its applications in game AI are mainly based on game scores, which can be normalized in three ways: comparing to a reference score, normalizing with a baseline, and inter-algorithm normalization [21]. Peer confrontation refers to evaluating agents by playing against other players. For comparison among numerous players, it usually uses standard rating systems such as Elo [22] and Glicko[23]. And human assessment refers to evaluating agents subjectively and qualitatively with the help of humans. The best known and most commonly used methods are the Turing Test [24] and its variants. It can be classified into two subtypes: first-person assessment and third-person assessment, according to whether the judger plays games with the agent. And there are some researches on the evaluation of game agents based on the Turing test. In terms of first-person assessment, Soni et al. [25] use a "Turing test" method in a first-person shooter named Unreal Tournament 2004. In this method, the human judgers play games with three different agents respectively and are given a questionnaire with Likert scale [26] after each game to evaluate the agent in four aspects: perception of humanness, predictability, entertainment value, and challenge. And finally, they are also asked about their overall experience, like "which agent did you enjoy the most". Also in this game, Hingston [27] uses another "Turing test" method, in which each human judger is asked to play against one human player and one agent, and then give evaluations on the two opponents' humanness scale. These two methods both have the risk of identity leakage (the human judger knows there is an agent playing against him), which may influence the evaluation results. The work described below has no such risk. The first-person assessment in StarCraft [28] requires the human judger to play with an agent opponent and evaluate the agent using Likert scale from "very bad" to "very good" on seven aspects such as human likeness, decision making, operation and so on. And the third-person assessment in Quake II [29] requires the human judger to watch the game videos, and then mark the identity of each player (human or agent). At present, the evaluation of wargame agents mainly uses the method of peer confrontation, which cannot fully demonstrate the decision-making level of agents and may promote utilitarian confrontations. Therefore, we introduce the human assessment method into the wargame and use a "Turing test" method to evaluate wargame agents comprehensively. And at the same time, considering the high cost of labor, we propose a data mining method as an alternative.

III. The MiaoSuan Platform

A. *The Architecture*

As shown in Figure 1, the proposed MiaoSuan platform consists of five main parts: game engine, player modules, intelligent scheduling management module, service module, and data storage and application modules. Next, we will expatiate each part respectively.

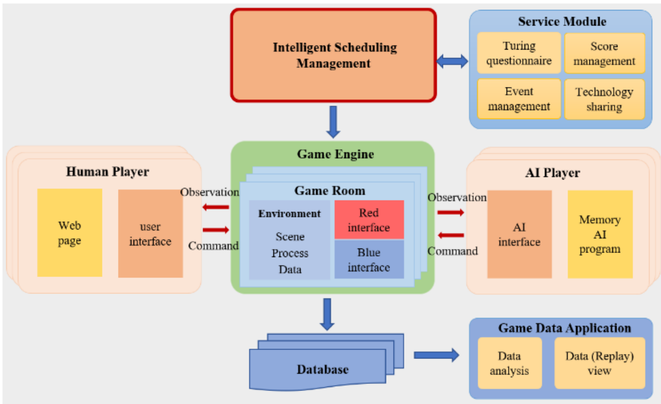


Fig. 1. The architecture of MiaoSuan

1) *Game engine:* The game engine can afford to run multiple game rooms parallelly. Each room runs an independent confrontation involving multiple players, which consists of the game environment and the interfaces of all factions (one faction can have one or more players). For example, the land wargame has two factions named red and blue, so each room contains two interfaces: red interface and blue interface. These mean that the platform uses the engine to manage multiple rooms and uses the game room to manage each confrontation, which helps to focus on the game logic in one confrontation with less dependence and also helps to isolate abnormalities to improve the stability of the platform.

The game environment not only refers to the basic game scene but also includes the moving of game process and the generation of game data.

For the game scene, it is one of the scenes of one of the subsidiary platforms. MiaoSuan platform contains many types of subsidiary platforms with different backgrounds. At present, it has accessed to seven different subsidiary platforms including the land wargame, the sea wargame, and the air wargame. The game scenes in each sub-platform are diverse, which can be adjusted by parameters flexibly. For example, the parameter 'scale' can adjust the scale of the game among mini level, squad level and group level, the parameter 'map' can be selected from dozens of maps to adjust the game's terrain, and the parameters in the scenario file can be changed to adjust the specific configuration of the game. It is the

[8] http://www.ciccwargame.com/h-col-101.html

[9] http://www.hexwar.cn/index.html

convenience of adjusting parameters that brings great flexibility to the platform.

For the moving of game process, there is an environmental management unit pushing the game progress until the game is over. It judges the players' actions based on game rules and then generates a new state. This unit has two work modes: online confrontation mode and offline training mode. In the online confrontation mode, considering the requirements of high concurrency and stability, the management unit is designed as the master control. It runs independently driven by time and sends observation data according to the time tick regardless of players' actions. In contrast, in the offline training mode, players occupy the center stage. So the management unit is driven by events to be easy to train agents. It pushes the game step by step. Only after all players in the game have made action decisions can the game move forward.

And for the generation of game data, the game environment quantifies game states by structured data. It records the game data in JSON format once a second and finally generates its replay data which has many frames. Each data frame includes fourteen kinds of information. Their details are available in our platform. In addition, because the game is imperfect, each player can only observe partial information. The game environment can also process the game data into different views and broadcast them to the corresponding factions' interface.

In addition to receiving the partial data from the game environment, the interfaces in the game rooms also send the structured action data to the game environment to change its state. The red interface sends action data from players of the red faction, and the blue interface sends action data from players of the blue faction. In other words, the players' identity information is only kept in the player modules. The game room only knows there are two factions playing the game, but does not know who they are. The game environment communicates with them only through the corresponding interfaces.

2) *Player module:* The platform supports the access of human players and AI players. Both the human player module and the AI player module consist of the client end and the standard interface.

For the client end, human players adopt a web-based human-computer interface to realize the operations of observing game states and issuing action commands. While AI players obtain game observations by reading the real-time game data from the AI interface and issue action commands by sending structured data with selected action types. At present, the platform has launched several high-level agents such as AlphaWar, DemoAI, and Mandalorian. They can be algorithms based on domain knowledge, models trained by machine learning methods, or the combination of the two.

For the user interface, it is the communication pipeline between human players and the game engine. It is connected to the interface of this human player's faction in the game engine. From the game engine to the user end, it receives and parses the partial game data, and then displays them graphically on the computer screen. And from the user end to the game engine, it converts the click operations on the computer screen into structured action data and then sends them to its corresponding interface. Figure 2 shows the graphical user interface of the land wargame. In the interface, the left side shows the pieces of our faction. The content in the lower left corner displays the position and elevation of the designated grid. The middle part shows the pieces' positions and actions. The upper right corner shows the game time and some ancillary functions. The right side displays the real-time scores and executed actions' effects. And the lower right corner is the operation area, showing the executable actions and options of the designated piece. Meanwhile, the selection of actions can also be realized by right clicking on the designated piece.

Fig. 2. The graphical user interface of the land wargame

For the AI interface, it is the communication pipeline between AI players and the game engine. It is connected to the interface of this AI player's faction in the game engine. This interface also has the functions of parsing partial game data and sending action data. But there is no need for graphical displays like the user interface. Furthermore, another important function of this interface is to provide a standard protocol for the development and access of AI. The protocol standardizes five basic methods used for the interaction between the AI players and the game engine (their source code and detailed description are available in our platform) :

- Setup (setup_info) to obtain the basic information of the environment so as to initialize the AI algorithm.
- Step (observation) to analyze the received observation data and output the action list after decision-making. It supports the application of planning algorithms and learned forward models.
- Reset ( ) to free up the resources such as data and models used by AI in the game.
- Deploy (observation) to deploy pieces' actions before the game timer starts.
- Command (observation) to group pieces and assign corresponding game tasks to them. Only the leader AI can use this method.

The setup (setup_info), step (observation), and reset ( ) are indispensable to the access of AI, while the deploy (observation) and command (observation) are optional. When an AI player participates in a game, it firstly calls the setup method to get the game's information such as the scenario, the faction, and the role of the AI player. And then if the AI takes a leading role in its faction, it can call the command method to group other players and assign combat directions and missions to them. And if the AI player needs to do some deployments for its own pieces, it can call the deploy method. Then, the game begins formally, the AI player calls the step method again and again to release its cognitive and decision-making capacity. Until one faction wins or the game time is reached, the game ends. The AI player calls the reset method to free up its resources.

3) *Intelligent scheduling management module:* This module is mainly used in the working modes without human managers. There are no human managers governing the game room, so the intelligent scheduling management module acts as the "room-owner" to perform the operations of creating the game room, selecting the game environment and aligning players' factions. It also plays a central role in the evaluation stage, which is especially important in the Turing test mode. It automatically schedules the test according to the test plan from the event management module. Under its scheduling, other modules can work coordinately to finish the test and obtain the final test results.

4) *Service module:* This module contains multiple subsidiary modules, which provide colorful functions for the platform. They are either necessary for the confrontation and evaluation or have great practical value in application. Here, we describe four of them in detail.

a) Turing questionnaire module: This module is used to enrich the method of AI evaluation. Guided by the Turing test, this module interacts with humans and collects their assessments about game players by questionnaires. With reference to some Turing test variants [25][27][28][29] and domain knowledge of wargame experts, the questionnaire is designed to contain two parts: guessing the identity of players (human or AI) and judging the performance of players from various aspects. For example, they can be the ability of resource utilization, environment perception, and strategy planning. Each aspect contains many detailed items and each item has multiple choices in the form of 5-point Likert scale.

b) Score management module: This module is used to store and manage the scores of each player. It consists of two sub-modules: score storage unit and score statistic unit. The storage unit stores the judged scores from the game engine, the replay analysis scores from the game data application, and the Turing evaluation scores from the Turing questionnaire module. The scores of all players in the platform will be preserved in this module. And the statistic unit calculates each player's comprehensive score based on its performance in each game and then ranks all players according to the final score. It provides the total points of judged scores, the average score of replay analysis scores, and the average score of Turing evaluation scores. At the same time, it also provides the probability that an AI is guessed as a human player, which is usually used to test the intelligence level of AI.

c) Event management module: This module is used in competitions. It takes the number of participants as input and automatically generates a schedule for the competition. It usually adopts the round robin system with double cycles to ensure fairness among players. And then, it will send the schedule to the intelligent scheduling management module.

d) Technology sharing module: This module is set to share human-computer gaming technologies and accelerate the development of this field. We share a Software Development Kit (SDK) and an AI algorithm with simple strategy to give reference to AI developers. We also share some high-quality datasets which can be used for research directly.

5) *Game data storage and application:* After each game, the game engine will directly send the global game data (also called replay data) to the database. The replay data is stored in the form of compressed JSON file. Each file contains many frames of data, whose amount is determined by how long the game lasts. When the replay data is needed, it can be transmitted to the data application module. This module is developed aiming to make full use of game data. It can be composed of many sub-modules with different functions. Here we present two basic sub-modules, one for reviewing and another for analyzing. The reviewing sub-module provides services for showing replay data graphically and identifying critical branch points in the game. And the analyzing sub-module provides services for narrative construction and gameplay evaluation, which will be used to enrich the method of AI evaluation.

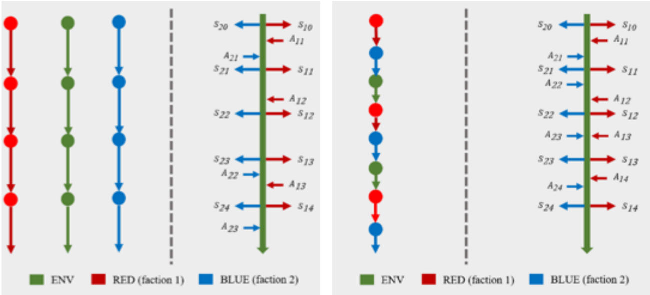
B. The Workflow of Different Game Modes

The platform provides many types of game modes, including online confrontation mode and offline training mode. It also provides a Turing test mode, which is used to evaluate agents through human vs. computer and computer vs. computer online confrontations. In the online confrontation mode, humans can play games with other human players, and also can play games with built-in agents in a hostile or cooperative relationship. Besides, they can also let their own agents compete with built-in agents. These lead to four different sub-modes: human vs. human, human vs. computer, human/computer hybrid, and computer vs. computer. Differently, the offline training mode only has the form of computer vs. computer. And under different working modes, the workflow of the platform is different. Table I shows the modules required in different working modes.

TABLE I. DIFFERENT MODULES REQUIRED IN DIFFERENT MODES

Mode	Sub-mode	Modules
Online confrontation	human vs. human	Game Engine, Human Player, Score management, Database
	human vs. computer	Game Engine, Human Player, AI Player, Score management, Database
	computer vs. computer	Game Engine, AI Player, Score management, Database, Intelligent Scheduling Management
	human /computer hybrid	Game Engine, Human Player, AI Player, Score management, Database
Offline training	computer vs. computer	Game Engine, AI Player, Intelligent Scheduling Management
Turing test mode		Game Engine, Human Player, AI Player, Turing questionnaire, Score management, Database, Event management, Data analysis, Intelligent Scheduling Management, Data (Replay) view

1) *Online confrontation mode:* This mode works as a real-time strategy game. In this mode, the moving process of the game environment is driven by time independently. As shown in Figure 3(a), the red faction, blue faction and the engine ruling are three independent processes. The engine pushes the game process independently according to the clock, which is not affected by players' actions. It sends game observations to corresponding factions every second and performs continuous polling to discover actions from players. When receiving an action, the engine judges the action's effects and updates the current state based on this action. It is worth noting that the clock can be accelerated. The clock speedup of 5 means that the environment engine makes a step forward every 200ms.



(a) online confrontation (b) offline training

Fig. 3. The moving process in different modes

As mentioned above, this mode can be divided into four subsidiary modes according to the identity of players. The modes with human players are managed by the human room-owner, while the mode without human players is managed by the platform's intelligent scheduling management module. Here, we will take the human vs. computer confrontation as an example to introduce the workflow of the platform. The human vs. human confrontation can be easily implemented by replacing the agent with a human player. And the workflow of computer vs. computer confrontation is roughly the same as the offline training mode introduced below, except for the environment's moving process.

a) The human player logs in to the MiaoSuan platform through its web page.

b) The human player selects the parameters of his expected game environment and then creates a corresponding game room.

c) The human player selects a built-in agent as his opponent and sets its faction.

d) The two players enter the game room. And the user interface and the AI interface are connected with their corresponding faction's interface in the game engine.

e) Execute the initialization function of the environment to generate an initial state, and also execute the setup function of the agent.

f) The game starts and the environment moves forward and generates new observations according to the clock.

g) The red player and blue player make decisions according to their real-time observations.

h) The environment judges the action's effects when receiving the player's action.

i) Steps g)-h) run repeatedly until the game ends.

j) The game engine stores the game data in the database. And the score management module reads and stores the final judged scores of each player.

k) Execute the reset function of the environment and the agent, then release the game room.

2) *Offline training mode:* This mode is used for agent learning, which manifests in the form of computer vs. computer confrontation. There is an opponent pool with many capable agents. Each of them can be used as the opponent of the training agent. In each round of training with each opponent, the moving process of the game environment is driven by events. As shown in Figure 3(b), the red faction, blue faction and the engine ruling are one series process. In each step, the environment will wait for all players' actions. Only after judging all actions' effects can the environment engine make a step forward.

The workflow of the platform in the offline training mode is as follows. There is a training agent and an opponent agent participating in the game. Each of them corresponds to one faction.

a) The intelligent scheduling management module creates a game room according to the set parameters.

b) Instantiate the environment and players in this game room, and connect the AI interfaces of the two agent players with their corresponding faction's interface in the game engine.

c) Execute the initialization function of the environment to generate an initial state, and also execute the setup functions of the two agents.

d) Execute the step function of the red agent to get its actions.

e) Execute the step function of the blue agent to get its actions.

f) The environment receives and judges the actions from red and blue factions, and then makes a step forward to generate a new state.

g) If the game is over, execute step h), otherwise repeat steps d)-g).

h) The game engine stores the game data in the database.

i) Execute the reset function of the environment and the two agents, then release the game room.

3) *Turing test mode:* This mode performs the "Turing test" through an official double-cycle competition among high-level human players and the agents to be tested. Every two players can meet as opponents and every two players will conduct two games in different factions (after one game, the two players exchange their factions). Once the participants and game environment have been set, the whole competition can be conducted almost automatically by the platform except for the human assessment. It provides the first-person "Turing test" assessed by the human players and the third-person "Turing test" assessed by the invited domain experts. The workflow of this mode is as follows:

a) Select the human and AI players participating in the "Turing test".

b) The event organizer inputs the players' information, AI program packages and the parameters related to the game environment to the event management module.

c) The event management module generates a schedule for this double-cycle competition and sends it to the intelligent scheduling management module.

d) When all players are ready for beginning the competition, the user interface and AI interface will anonymize the players' identities.

e) The intelligent scheduling management module starts the game engine as required to begin the competition. It creates many game rooms to perform online confrontations among all players. It lets all players enter their corresponding game session directly to begin their first game. After that, it swaps the two players' factions in each room to begin their second game.

f) While the game is going on, the data (replay) view module reads real-time game data from the game engine and show them graphically to the domain experts.

g) After each game, the game engine stores the game data in the database. And the score management module reads and stores the final judged scores of each player.

h) After games in one room are over, the Turing questionnaire module sends questionnaires to the human players and expert viewers to collect their evaluations and then sends the evaluation results to the score management module.

i) The score management module counts the composite scores of each player, which includes the total points of the judged scores, the average evaluation scores of the first-person "Turing test", the average evaluation scores of the third-person "Turing test" and the misjudgment rate of AI's identity.

C. *AI Evaluation Method Based on the Turing Test*

The most basic and commonly used evaluation metric to test AI is the score judged by game rules. It can be the AI player's total score or the net score relative to its opponent. However, it is not comprehensive to evaluate AI only using this metric. Because of the uncertainty of environments and the intransitivity of strategies, the same gameplay may win in one game and lose in another. This makes decision-making problems usually focus on the process rather than the result [30]. The judged score cannot reflect the quality of AI's decision-making ability in the game. Therefore, we provide an AI evaluation method based on the Turing test. It collects the evaluation results from humans by electronic questionnaires. Figure 4 is an example of questionnaire design. The questionnaire can be responded by human players. If there are human players in the room, the platform will send questionnaires to them separately after games to let them evaluate their opponents. At the same time, the questionnaire can also be responded by viewers who watched the games. The platform will send questionnaires to all viewers separately after games to let them evaluate all players in the room.

Name		Occupation		Room ID	
Players		Red ID:		Blue ID:	
Is it AI		Yes☐ No☐		Yes☐ No☐	
Play style		1☐ 2☐ 3☐ 4☐ 5☐ Conservative Radical		1☐ 2☐ 3☐ 4☐ 5☐ Conservative Radical	
Resource utilization	Weapons	1☐ 2☐ 3☐ 4☐ 5☐		1☐ 2☐ 3☐ 4☐ 5☐	
	Pieces	1☐ 2☐ 3☐ 4☐ 5☐		1☐ 2☐ 3☐ 4☐ 5☐	
Environment perception	Judgement	1☐ 2☐ 3☐ 4☐ 5☐		1☐ 2☐ 3☐ 4☐ 5☐	
	Sensitivity	1☐ 2☐ 3☐ 4☐ 5☐		1☐ 2☐ 3☐ 4☐ 5☐	
Strategy planning	Action coordination	1☐ 2☐ 3☐ 4☐ 5☐		1☐ 2☐ 3☐ 4☐ 5☐	
	Tactical rationality	1☐ 2☐ 3☐ 4☐ 5☐		1☐ 2☐ 3☐ 4☐ 5☐	
	Tactical novelty	1☐ 2☐ 3☐ 4☐ 5☐		1☐ 2☐ 3☐ 4☐ 5☐	
Remarks					

Fig. 4. Example of Turing questionnaire design

The necessary condition of the Turing test is that the person filling out the questionnaire does not know the identities of the subjects. Therefore, we have some special treatments for the platform to create a blind test environment. The operations are as follows:

- The user interface and the AI interface not only filter out the information related to the player's identity but also rename the player's nickname in a unified format (such as one is Player A, the others are Player B, Player C, …).
- The intelligent scheduling management module directly arranges for players to enter their game session, avoiding some conventional operations taken by players before the game, such as room creation and opponent selection.
- The web front-ends including the game end and the game data viewing end only display the unified names of players rather than their real nicknames.

Forethoughtfully, we propose a data analysis module with similar functions, given that the human especially domain experts cost is very high. In daily tests, AI developers can use this module as a substitute for human assessment. This module analyzes the replay data and quantifies the analysis results to evaluation scores. It mines the player's operations in the game, which can reflect the decision-making ability of this player. For example, the ability of resource utilization can be reflected by the ratio of used weapons and pieces, the ability of environment perception can be reflected by action frequency, and the ability of strategy planning can be reflected by the heat map of moving trajectory. Meanwhile, this module can also confirm the AI identity of the player according to some significant features. For example, if there are perverse operations such as multiple pieces acting at the same time, it can be confirmed that the player is AI. All in all, this method quantifies the qualitative analysis and can meet the demand of the "Turing test" efficiently and economically.

We have applied this Turing evaluation method to real-world competitions. Figure 5 shows an example of the third-person Turing evaluation results for six agents, which come from twenty-two domain experts. We can see that cognition and decision-making abilities have a strong correlation with identity characteristics. Consistent with the results of ability evaluation, player F is judged as an AI by all experts, and player E is judged as an AI by the vast majority of experts. And player D, the most humanoid player, has strong comprehensive ability especially in aspects of weapon utilization, terrain utilization and sensitivity.

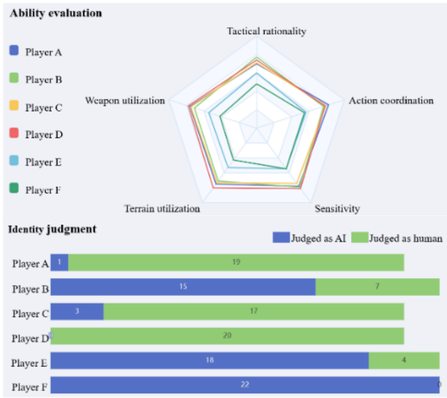


Fig. 5. Example of Turing evaluation results

IV. Application Of MiaoSuan

Since its official opening in November 2020, the platform has attracted users from all walks of life and has been widely praised. Next, we will go into detail about its applications.

A. *Current Usage*

So far, there are seven subsidiary wargame platforms interfaced with MiaoSuan. They are heterogeneous and independent of each other and only connect with the MiaoSuan platform. And at present, MiaoSuan has 14739 human users and 290 AI players. They come from many types of organizations such as enterprises, universities and research institutes. There are 120437 games in total supported by the platform, of which 75.49% are human vs. computer confrontations. In addition, the opened AI SDK and datasets in the platform have been downloaded more than a thousand times.

B. Competitions on the MiaoSuan Platform

The platform has complete event management function and has supported various types of events: (1) the large-scale national and provincial competitions which have demanding requirements of the platform's load capacity, stability and concurrency. (2) the AI test competitions which have more flexible scenarios aiming to test the intelligence level of agents. In these competitions, we will invite domain experts to conduct authoritative "Turing test". (3) the normal AI competition which holds computer vs. computer round-robin every week. It aims to promote the long-term and sustainable development of intelligent game technologies.

V. Conclusions And Future Work

In this work, we present MiaoSuan, an integrated platform for imperfect information game research. It provides an open architecture for wargame implementations and supports the access of multiple game environments and agents. It also has abundant functions such as human-computer confrontation, AI development and training, technology sharing, and event management. In addition to the platform, considering the difference between cognitive intelligence and perceptual intelligence, we propose a human assessment method for wargame agents based on the Turing test and an alternative data analysis method, aiming to enrich the methods of evaluating decision-making agents. The "Turing test" process can be scheduled automatically by the platform based on its human-computer confrontation function.

In the future, we will continue to improve our platform. We will add sub-platforms that have associated environments such as the aero-amphibious wargame platform. And we will upgrade the environments of teamwork mode by simulating communication interruption and stopping information sharing. All in all, we will consistently be committed to constructing the human-computer gaming ecosystem and hope MiaoSuan will facilitate further studies in the domain of imperfect information game.

Acknowledgment

The authors would like to thank the researchers and users of the MiaoSuan platform and the participants of the competitions for their work. This work is supported by the Strategic Priority Research Program of Chinese Academy of Sciences, Grant No. XDA27000000.

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