# High-performance Algorithms using Deep Learning in Turn-based Strategy Games

Tomihiro Kimura and Ikeda Kokolo
*Japan Advanced Institute of Science and Technology, JAIST, Ishikawa, Japan*

Keywords: Turn-based Strategy Games, Deep Neural Network, Deep Reinforcement Learning, Policy Network, Value Network, AlphaZero, Residual Network.

Abstract: The development of AlphaGo has increased the interest of researchers in applying deep learning and reinforcement learning to games. However, using the AlphaZero algorithm on games with complex data structures and vast search space, such as turn-based strategy games, has some technical challenges. The problem involves performing complex data representations with neural networks, which results in a very long learning time. This study discusses methods that can accelerate the learning of neural networks by solving the problem of the data representation of neural networks using a search tree. The proposed algorithm performs better than existing methods such as the Monte Carlo Tree Search (MCTS). The automatic generation of learning data by self-play does not require a big learning database beforehand. Moreover, the algorithm also shows excellent match results with a win rate of more than 85% against the conventional algorithms in the new map which is not used for learning.

## 1 INTRODUCTION

Games such as Chess, Shogi (Japanese Chess), and Go have long been used as test cases in artificial intelligence (AI) research. Currently, AI agents for Chess and Shogi have been developed that can perform beyond the professional level of humans. In contrast, it was initially thought that making an AI with professional Go player-level agents is difficult; however, in 2016, AlphaGo (Silver et al., 2016) was released, which is the first program to beat professional Go players at full board size without a handicap. Following the success of AlphaGo, DeepMind released AlphaGoZero in 2017 (Silver et al., 2017), which is and improvement of AlphaGo by not requiring data to be learned from previous games. Instead, AlphaGo Zero learns by only playing against itself making it stronger than all previous versions. That same year, AlphaZero, a general-purpose version of AlphaGo Zero (Silver et al., 2018), was released, that masters the games of Chess, Shogi, and Go. Since then, the development and research of game AI that incorporates deep learning and reinforcement learning have been popular.

Turn-based strategy and war simulation games have been popular in the board and video game market. However, AI programs for turn-based strategy games have not been able to satisfy the level of human players, because of the following two reasons.

Firstly, turn-based strategy games have a vast search space, which is larger than Go or Shogi. Hence, even the first turn could lead to a computational explosion. Secondly, the complexity of the game system makes programming difficult. These problems are caused by a variety of factors that make gaming systems complex and engaging.

One of the factors that complicate games is the variety of pieces and the various characteristics of topographic elements; these pieces and topographic features do not exist in Go or Shogi. Moreover, the initial layout of the map is not fixed as in Go and Shogi, and a wide variety of maps can be designed in many cases.

Furthermore, in turn-based strategy games, all units can sequentially operate during a turn, providing more options and making this condition more susceptible to computational explosions.

In addition, board game researchers who study Go, Chess, and Shogi have accumulated game data through many years of research, which is not the case for most turn-based strategy games; hence, researchers have to gather the data themselves if necessary.

Deep learning, which is used in AlphaGo, is becoming very popular and is expected to be used as a



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search technique for games with huge search spaces far more complex than Go and Shogi. AlphaZero's algorithm, although called MCTS, is quite different from the traditional MCTS algorithm. AlphaZero uses the probabilistic output of the policy network as a guide for proceeding with the search. It is considered to be general and can be applied in cases where the original MCTS algorithm is applicable. Hence, it would be interesting to evaluate the performance of AlphaZero's algorithm on other games.

In this paper, we evaluate the performance of AlphaZero's algorithm in terms of the difficulty and ingenuity in applying it to complex games and of its ability to accelerate learning.

The original name of the algorithm is APV-MCTS (Asynchronous Policy and Value MCTS). We modify it here by removing the element A; hence, our algorithm is called PV-MCTS.

## 2 TUBSTAP

To address the difficulties stated above, we use the Turn-Based Strategy Games as an Academic Platform (TUBSTAP) (Fujiki et al., 2015), which allows the development and comparisons of the performance of turn-based strategy game AI agents. The game rules are examined, extracted, simplified, and abstracted from the rules of various turn-based strategies such as "Famicon Wars". Hence, the basic operation of the turn-based strategy game can be investigated on this platform.

### 2.1 TUBSTAP Game Rules

The following units are available in TUBSTAP: Infantry, Panzer, Cannon, Anti-air Tank, Fighter planes, and Attack Aircraft. In addtion, six types of terrain cells are available: mountain, forest, plain, road, sea, and fortress. All units have an initial hit point (HP), which is an integer between one and ten such that the unit is, removed from the board when it reaches an HP of 0. The HP decreases when units attack; simultaneously, the HP of the attacking side unit decreases during a counterattack. TUBSTAP is similar to "Famicom Wars". The game progresses by having fighting RED and BLUE forces fight each other with multi-unit movements in one turn. The match ends when either units are completely destroyed, or the specified number of turns is reached. The winning side is the one that destroys the other unit or has a higher total HP above a threshold value specified at the end of the game.

### 2.2 TUBSTAP Game Maps

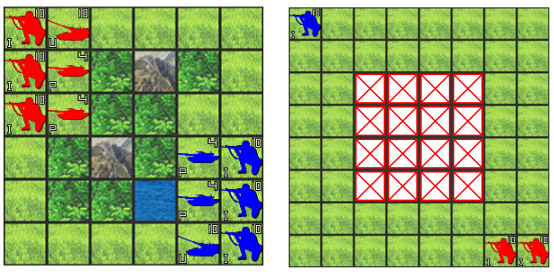
TUBSTAP users can create and test a wide variety of maps. Figure 1 (a) shows an example of a battle map in TUBSTAP, which is used in game competitions and AI combat capability. Although the map size is relatively small, i.e., $6 \times 6$, current AI programs used on this map still have difficulties in selecting the optimal operation. In fact, there are no algorithms that can perform better than the level of humans except for the MCTS-type algorithms, which has been found to perform satisfactorily. On this map, it is difficult for an AI program to always select the optimum operation, and sometimes it selects the operation which is very disadvantageous. There is no algorithm beyond human action. Among the game algorithms, the MCTS type algorithm is the only one that seems to be able to operate competitively.

We prepared a collection of benchmark problems (Kimura and Ikeda, 2016) in AI research, including pathfinding problems, tracking problems, and multi-unit cooperation problems, with varying levels of difficulty. Figure 1 (b) shows an example of benchmark maps, representing the pinch problem (sandwich problem). In the pinch problem map, the search algorithm has to search deep and wide ranges to obtain the right answer, which is difficult to read accurately.

Considering reasonable learning time and execution time, the map size is set to $6 \times 6$, and all evaluations are made on maps of this size.

### 2.3 Previous Works

The algorithms applicable to TUBSTAP are limited by the computational complexity of turn-based strategy games. Although MCTS and its variations (Kato et al., 2013) and the minimax method, which divides the aspects (Sato et al., 2015; Sato and Ikeda, 2016), have been found to be applicable, the obtained performance is still poor. A recent study has applied, deep learning to TUBSTAP (Kimura and Ikeda, 2019),



(a) Battle map example. (b) Pinch problem map.

Figure 1: TUBSTAP Map Examples.

which learns a large number of match records to create a policy network; however, it does not have a search method. In relation to this, a recent study developed a search method that combines a policy network and the value network introduced in AlphaZero (Kimura, 2019); however, detailed technical data and analyses are insufficient. This paper will provide a more detailed technical analysis of the scheme.

# 3 PROPOSED SYSTEM

The basic principles of the proposed system follow the AlphaZero's system but with changes incorporated for TUBSTAP. The changes include a function for multi-unit operations, an additional operation for searching attack nodes with priority, and a neural network with improved performance. The proposed system consists of a tree search part, a reinforcement learning part, and a neural network part.

In the learning part, data are generated by the search of PV-MCTS. In the normal game play phase, the final next move is decided by the search based on the prediction of the learned neural network.

## 3.1 New Design Part

Many parts of this research are added to the AlphaZero design. To solve the complex data structure problem of the turn-based strategy game, change the output structure of the neural network and move the unit designation from output to input. We try to simplify complex games by incorporating a structure for selecting multiple units into the search tree. To speed up node selection in the MCTS, we introduce a bias term to make the search efficient. Introducing new knowledge to change the design of neural networks, aiming for a design that converges faster.

## 3.2 Tree Search Design

The PV-MCTS search is an MCTS-type search that uses deep neural networks with both policies and values. The search proceeds based on the probability distribution vector p output of the policy network and node selection by simulation. The node with the highest visit count is selected. Note that search does not use the rollouts commonly used in MCTS. During self-play, the node is reused for the next search.

In simple TUBSTAP output representation, unit selection and action should be in the output, but in this study, the unit selection is placed on the input side and included in the tree search. Figure 2 shows that the selection of units is performed simultaneously by node selection using predictor upper confidence bound applied to trees (PUCT) (Silver et al., 2017; Rosin, 2011) values. When the number of units is one, the algorithm is the same as the usual PUCT search. We assume that the action $a_{i,j}$ is a pointer for each unit $u_i$ of TUBSTAP, and the aspect represented by each node transits to the aspect of the next node through the edge $a_{i,j}$. Child nodes are expanded individually for each $u_i$ as shown in the boxed area in Figure 2, and unit selection information is included in the selected node. If there are n units on the map, the search is performed n times and all units are selected.

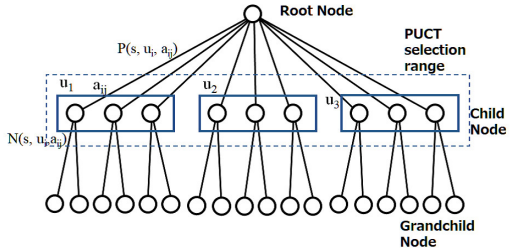



Figure 2: Node selection range.

To select a node to search: For all possible action nodes of the unit, calculate the PUCT value according to the following formula and select the node with the largest PUCT value.

$$PUCT(s,u_i,a_{ij}) = Q(s,u_i,a_{ij}) + Cpuct P(s,u_i,a_{ij}) \frac{\sqrt{\sum_b N(s,b)}}{1+N(s,u_i,a_{ij})} + \frac{B_{attack}}{1+N(s,u_i,a_{ij})} \quad (1)$$

$$a_{i,j},\ u_i = \arg\max_{a,u}(PUCT(s,u_i,a_{ij})) \quad (2)$$

Here, $Q(s,u_i,a_{ij})$ is the mean action value, $Cpuct$ is an exploration constant set to 0.8, $P(s,u_i,a_{ij})$ is the prior probability, $N(s,u_i,a_{ij})$ is the visit count of node, and $B_{attack}$ is a newly introduced term for accelerating learning, experimentally determined to be 3.7, which is used so that attack nodes are searched preferentially. The $B_{attack}$ term operates during both learning and normal operation. The effect of this term will be compared later in the experiment.

Dirichlet noise for a wide range search is added but only to the root node of the search tree. A Boltzmann probability selection with temperature decay is carried out in deciding the move for self-play.

The information stored in each node includes the number of visits $N$, the selection probability $P$, the total value $W$, the average value $Q$, value network output $v$, and the links to the child nodes of the node.

After the search reaches the game end, the number of visits and the value are updated by $N(s_t,a_t) = N(s_t,a_t)+1$, $W(s_t,a_t) = W(s_t,a_t)+v$, $Q(s_t,a_t) = \frac{W(s_t,a_t)}{N(s_t,a_t)}$. The node with the most visits in the last stage of the search becomes the next move.

## 3.3 Reinforcement Learning Design

Self-plays start from various initial maps and continue through PV-MCTS until the game state reaches a terminal node. The game state **s** and the probability distribution $\pi$ obtained by the tree search and the value $v$ by the game result $z$ are stored in the replay memory (Mnih et al., 2015), and the neural network is periodically learned. Note that $z = 1$ if the game is won, $z = -1$ if the game is lost, and $z = 0$ if the game is a draw. Based on randomly sampled data from the accumulated reply memory, learning is performed to minimize the loss function by a gradient method as described later. To enrich data and prevent bias in the neural network, rotation, and mirror data augmentation are performed.

## 3.4 Neural Network Design

The design of the AlphaZero neural network is modified in several ways to meet the game's specifications. For the input, the map terrain data, the unit position and HP data, and the data of the moved unit are encoded and normalized from 0 to 1. In this study, the map size is fixed to 6 x 6 and the data consists of 5 layers, so the input data form is $6 \times 6 \times 5$.

The data output from the Residual part is divided into a policy head part and a value head part. The policy output unit expresses a probability obtained by combining a movement destination position for expressing an operation of the unit and a position for expressing an attack. The output of the value head is a scalar value of [-1,1] and uses *tanh* as the activation function, which predicts the outcome of the game.

### 3.4.1 Output Data Representation

In this research, $36 \times 36 \times 5 = 6480$ output neurons are required when the data of (acting unit position) $\times$ (moving destination position) $\times$ (attack direction) representing the unit behavior is considered. However, as proposed in this study, the number of output neurons is reduced to $36 \times 5 = 180$ by moving the unit selection from output to input. A recurrent network can be used to reduce the number of output neurons (Kimura and Ikeda, 2019); however, the integration of the value network is difficult.

### 3.4.2 Neural Network Block

In the neural network block, the Conv2D layer on the input layer is connected to the Residual part. The Residual part has 8 identical Residual blocks with shortcut connections as shown in Figure 3.

The filter size is 128 on the input layer and Residual layers, and batch normalization(BN) and ReLU units are provided. In the policy head section, after 180 affine layers, BN layers, and ReLU, the Softmax is used as the activation function. In the value head section, after BN and ReLU layers, there are 128 and 1 affine layers, and *tanh* function as an activation function.

The representation of the unit's action requires 6 x 6 = 36 cells in the destination representation, and four direction encoding in the attack representation, so that $36+36\times4 = 180$ cells are required in one-hot expression for a single unit.

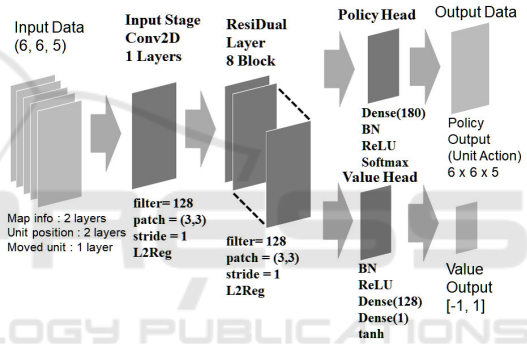



Figure 3: Neural Network Block.

### 3.4.3 Residual Network Block

A block diagram of the Residual Network (He et al., 2015) used in this study is shown in Figure 4. Although eight blocks of Residual layers are stacked after the input layer, backpropagation in learning is easily propagated by the shortcut connection of the Residual Network, which greatly improves the performance. To improve the convergence of learning, the using Wide Residual Network (Zagoruyko and Komodakis, 2016) is used as a reference and, dropout is included in the central part. SeparableConv2D is used instead of the commonly used Conv2D to save memory and to increase speed. It is a combination of DepthwiseConv2D (Howard et al., 2017) and Conv2D and is written as SepConv2D in the graph.

### 3.4.4 Learning Setting

For the learning setting, the loss function is expressed by the following equation.

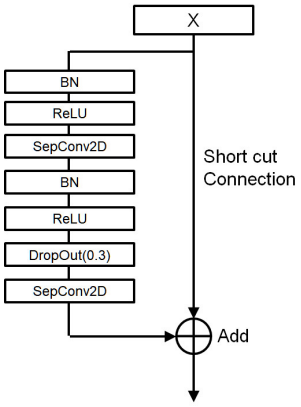



Figure 4: Residual Network Block.

$$loss = (z-v)^2 + D_{KL}(\pi \| p) + L2Reg \qquad (3)$$

Here, $D_{KL}(\pi \| p)$ is the Kullback–Leibler divergence, which is used to stabilize convergence. *L2Reg* is the L2 regularization term, where the coefficient is set to $1 \times 10^{-4}$. SGD + momentum with Nesterov option is used as the optimizer, and the moment term constant is 0.9. The batch size is 128.

# 4 EXPERIMENTAL RESULTS

This section describes the map group used for learning, the transition of learning loss, the effect of the Residual layer and the effect of parameters, the effect of long-term learning.

## 4.1 Learning Setting and Results

Comparisons of learning losses were performed to evaluate the adequacy of the design of the neural network part.

### 4.1.1 Learning Map Setting

In TUBSTAP, various terrains and units can be used, but in this paper, we limit it to $6 \times 6$ size maps where infantries fights in the plains. The maps used for the learning process in self-play were mixed with the following structure to simulate all situations and accelerate learning.

- Random maps. Random placement and configuration to cover diverse situations. Set HP and position randomly. The number of units is arranged in all cases to one vs one, one vs two, and two vs two (Figure 5 (a)) .
- Technical aspect maps. Maps that manually cuts out a situation where a specific procedure is required in an important aspect of the game as shown in Figure 5 (b).

### 4.1.2 Learning Curves

To compare the effect of the number of blocks of the Residual layer, learning of 4, 6, and 8 blocks were carried out on 500 learning maps, which is approximately 5000 iterations (because the maximum number of turns is set to 16, and approximately 8 to 16 turns are executed per game), are shown in Figure 6. Here, n represents the number of blocks of the Residual layer. The results show that n = 4 is slightly inferior, while n = 6 and n = 8 almost have equivalent losses.

Figure 7 compares the policy loss in the same learning for n = 8, 6, and 4. The results show that there is no apparent difference in policy loss for different n.

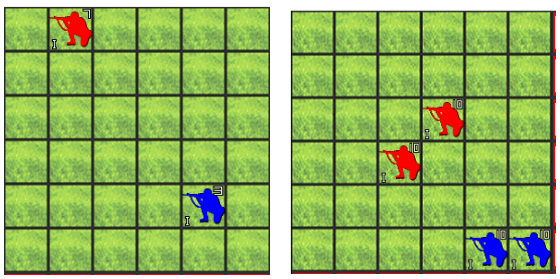
Figure 8 compares the value loss for n = 8, 6, and 4. The results show that n = 4 is slow to converge, degrades performance, and has an overall bottleneck performance.

To compare the performance of the Conv2D and SepConv2D parts in the Residual block, the learning curves are measured as shown in Figure 9 with Conv2D having n = 6 and SepConv2D having n = 8. The results show that both have similar performances. However, SepConv2D requires less working memory than Conv2D.

## 4.2 Experiments

Battle experiments were conducted to evaluate the performance of the learned neural network and PV-MCTS. The following two algorithms were employed as opponents.

- Primitive Monte Carlo (PMC). Simple Monte Carlo method without tree search. There are 100 rollouts until the end of the game.



(a) Random map. (b) Technical aspect map.

Figure 5: Learning Map Examples.

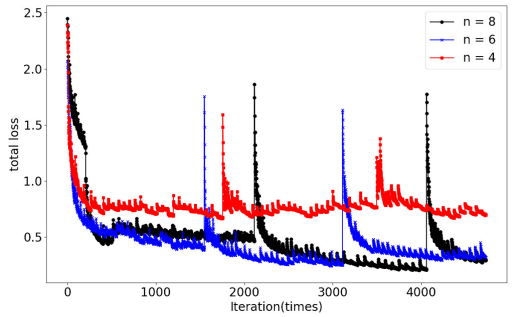



Figure 6: Total loss as of n = 8/6/4.

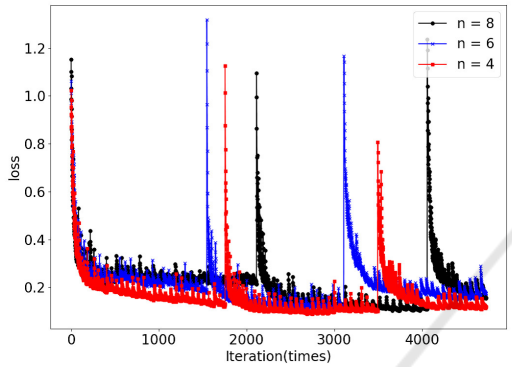



Figure 7: Policy loss as of n = 8/6/4.

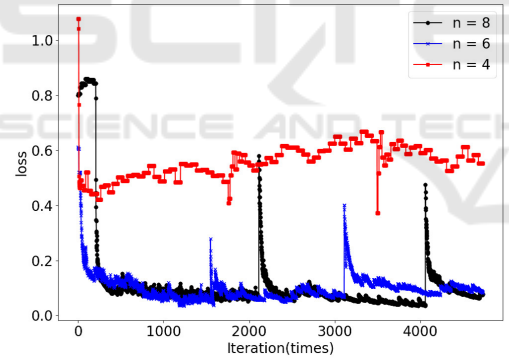



Figure 8: Value loss as of n = 8/6/4.

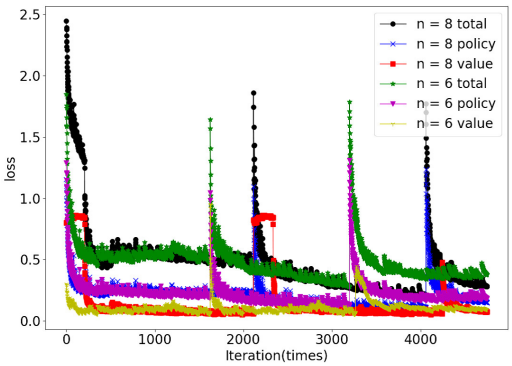



Figure 9: Loss of n = 8 Seq Conv2D and n =6 Conv2D .

- MCTS. One of conventional Monte Carlo tree search algorithm using the equation $UCB1 = number\ of\ wins/visit\ count + \sqrt{(\log(total\ visit\ count/visit\ count)}$. A total of 2000 simulations are performed by the rollout. The rollout continues until the end of the game, and if the number of visits to each node exceeds the threshold, the node is expanded.

An experimental battle map, Map01 is shown in Figure 10 (a). This map is unobstructed, has a size of 6 × 6, and has two infantry units on each side. This map is simple at first glance, but because it is a setting with many movement destinations, it is difficult to search and is suitable for the evaluation of our algorithm.

#### 4.2.1 Match Settings

The proposed PV-MCTS plays several games against one of PMC/MCTS. When using a map and playing $2n$ games on it, PV-MCTS plays Red side $n$ games, and Blue side $n$ games respectively.

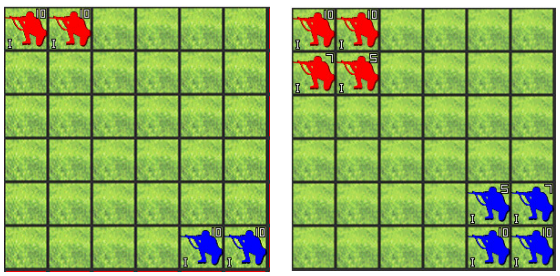
The game ends when either soldier is annihilated or when the number of turns reaches 16. If it is annihilated, the surviving side wins, and if the number of turns reaches 16, it is a draw. For PV-MCTS, 500 simulations are always reserved for searching.

To conform to the effect of long-term learning, the training time was set for approximately 3 weeks with the parameter setting considered to be adequate, otherwise, it was set to 500 games iterations as the short mode.

#### 4.2.2 Match Results in Map01

Table 1 shows the parameters in Map01 and the results of the game experiments. Here, n is the number of blocks in the Residual layer, time is the training time, Long denotes a game for approximately 3 weeks , and Short denotes 500 game iterations.

To investigate the effect of the number of blocks in the Residual layer, a battle experiment was performed with n = 8, 6, and 4. We find the performance of



(a) Map01. (b) Map02.

Figure 10: Experiment Maps.

Table 1: PV-MCTS match results in Map01.

| Opponent | Time | n | Sep/Conv2D | $B_{attack}$ | Dropout | Win | Draw | Lose | Win Rate(%) |
|---|---|---|---|---|---|---|---|---|---|
| PMC | Short | 4 | SepConv2D | 3.7 | Yes | 7 | 3 | 40 | 14.0 |
| MCTS | Short | 4 | SepConv2D | 3.7 | Yes | 3 | 5 | 42 | 6.0 |
| PMC | Short | 6 | SepConv2D | 3.7 | Yes | 18 | 5 | 27 | 36.0 |
| MCTS | Short | 6 | SepConv2D | 3.7 | Yes | 13 | 9 | 28 | 26.0 |
| PMC | Short | 8 | SepConv2D | 3.7 | Yes | 16 | 1 | 33 | 32.0 |
| MCTS | Short | 8 | SepConv2D | 3.7 | Yes | 11 | 4 | 35 | 22.0 |
| PMC | Short | 6 | Conv2D | 3.7 | Yes | 17 | 6 | 27 | 34.0 |
| MCTS | Short | 6 | Conv2D | 3.7 | Yes | 20 | 4 | 26 | 40.0 |
| PMC | Long | 8 | SepConv2D | 0.0 | Yes | 20 | 3 | 27 | 40.0 |
| MCTS | Long | 8 | SepConv2D | 0.0 | Yes | 24 | 2 | 26 | 48.0 |
| PMC | Short | 8 | SepConv2D | 3.7 | No | 7 | 3 | 40 | 14.0 |
| MCTS | Short | 8 | SepConv2D | 3.7 | No | 6 | 1 | 43 | 12.0 |
| PMC | Long | 8 | SepConv2D | 3.7 | Yes | 130 | 5 | 15 | 86.7 |
| MCTS | Long | 8 | SepConv2D | 3.7 | Yes | 128 | 6 | 16 | 85.3 |

the n = 8 type is relatively good. Moreover, the performance of Conv2D and SepConv2D in the Residual blocks, are approximately similar, but Conv2D requires more memory. The results show that the win rate in the long training time when $B_{attack} = 3.7$ is approximately half that when $B_{attack} = 0.0$, which confirms that the $B_{attack}$ term has an impact on the method's performance. In addition, the win rate is lower in the setting without dropout, which confirms that dropout must be added to improve the method's performance.

To verify the improvement of the performance after sufficient learning time, the result of continuing the training under the same condition for a long time is presented in the last row of Table 1, which shows a very high win rate.

### 4.3 Generalization Ability

As a final test, to evaluate the generalization performance of the neural network and determine its ability to cope with new situations, a battle was performed on a map that was not used for learning.

Table 2: PV-MCTS match results in map02.

| Opponent | Win | Draw | Lose | Win Rate(%) |
|---|---|---|---|---|
| PMC | 28 | 5 | 17 | 56.0 |
| MCTS | 24 | 5 | 21 | 48.0 |

Figure 10 (b) shows Map02 with a size of 6 $\times$ 6, which is not included in the learning map of four infantries at a time. The version of the neural network used has long term learning, has 8 Residual blocks with dropout, has SepConv2D, and has $B_{attack} = 3.7$. The match results are shown in Table 2.

Although Map02 is an new map for PV-MCTS, the method's competitive performance remains superior due to the generalization performance of the neural networks and the searching capability of PV-MCTS.

### 4.4 Discussion

Considering the result of experiments about the number of Residual blocks, it can be said that the number should be carefully set according to the experimental results. It was also shown that the performance of SepConv2D could be equivalent to the typical Conv2D convolution layer if set appropriately. The experimental data showed that the bias term introduced in the PUCT equation and the influence of dropout in Residual layer were effective in the search.

Although the performance of the long-term learning version was excellent, more effective methods of accelerating learning are desired because it is disadvantageous to have long learning times.

PV-MCTS performed well for battles in an new map not part of the learning process, which indicated the superiority of the algorithm. Considering that the number of simulations was only 500 for PV-MCTS, 3000 to 5000 for PMC, and 2000 for MCTS, PV-MCTS allowed effective search using the experience accumulated in neural networks.

## 5 CONCLUSIONS

The PV-MCTS algorithm, which combines a policy network and a value network introduced by AlphaZero, was applied to a turn-based strategy game to evaluate its performance. Besides, some modifications of algorithms were proposed and added to adapt to the difficulties of such games. The advantage of

PV-MCTS eliminates the need for a huge database of game records, reduces the burden of designing neural networks, and improves learning efficiency.

The design of the search tree had to be modified to allow the neural network to output complex data structures representing the actions of the units of turn-based strategy games. By moving the data of the operating unit from the output of the neural network to the input, we succeeded in significantly reducing the design load of the neural network. The unit selection problem necessary for the multi-unit operation peculiar to turn-based strategy games was also solved by integrating unit selection into the search tree. Effective changes such as SepConv2D, $B_{attack}$, and dropout were also introduced and evaluated. The number of blocks in the Residual layer was also evaluated.

The new method showed excellent performance as compared to two simple and classical algorithms. It also performed well on unlearned maps and showed generalization by learning. However, when the number of units was increased, the operation time increased, which is a problem that needs to be fixed in the future.

In future research, we aim to test the method on a wide variety of map situations and on maps with more units.

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