GOMOKU ALGORITHM STUDY

MIN-MAX AND MONTE CARLO APPROACHING

Authors: Jingtong Liu, Wei Sun, WeixunGe, GuochenXie

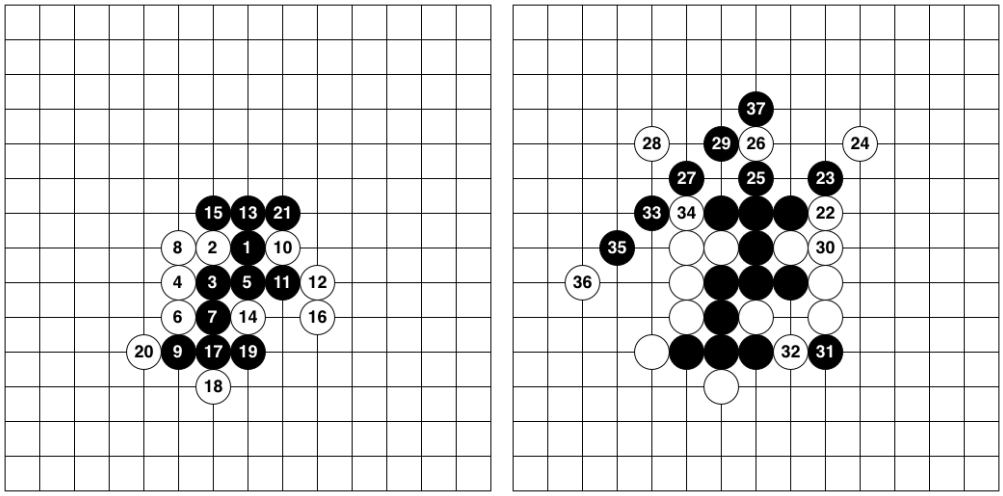
Abstract: In this project we are creating two gameplay agents for a popular board game Gomoku which can play against each other in order to compare two different approaches. One of them is implemented with Min-Max Search Tree algorithm and pattern as a classic algorithm for Gomoku, while the other is a combination of partial Min-Max search Tree, Genetic Algorithm, Monte Carlo search Tree. By using the second approach, we try to find an acceptable solution without searching all the way from top to the end in Min-max Tree. The latter approach has high research value when dealing with a huge search space. Comparing the performance of two agents, we discovered some interesting phenomenon and provided a possible explanation based on knowledge in both Computer Science and Gomoku.

Keywords: Gomoku, Min-Max, Monte Carlo, Genetic Algorithm**,** Modification.

INTRODUCTION

- **About the Game**

Gomoku is an abstract strategy board game, also called Gobang or Five in a Row, played on a board of 15X15 intersections. “Black plays first, and players alternate in placing a stone of their color on an empty intersection. The winner is the first player to get an unbroken row of five stones horizontally, vertically, or diagonally.” (Wikipedia)



Pic1: sample of the winning cases of the black stones

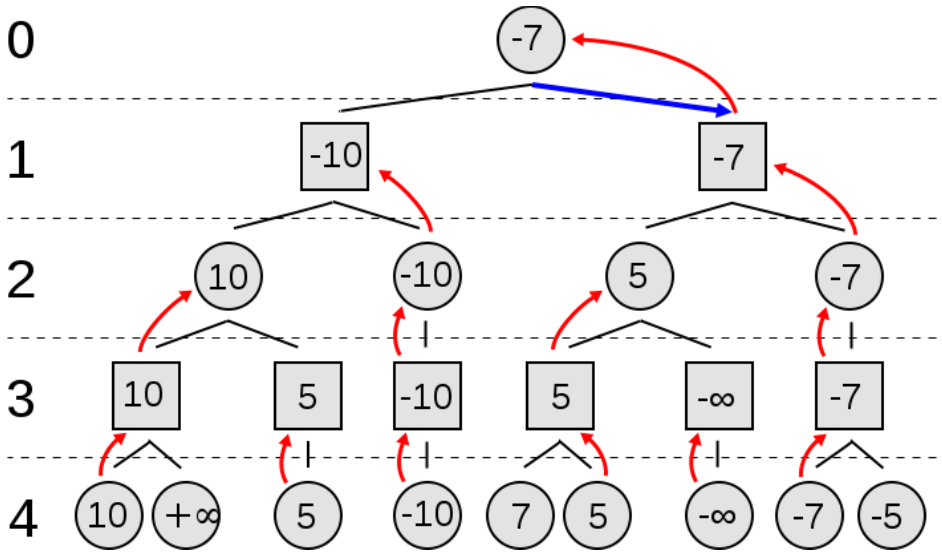
- **About the Algorithm**

Recently the study on Gomoku is focused on the pattern recognition combining with the Min-Max decision tree, mostly relying on the domain knowledge of the Gomoku experts. The complexity of the decision tree is 10^{70} , and any four-step forecast needs room of 10^{105}. As a result, how to optimize algorithm has become a challenging task. However, the more branches we want to cut off from the decision tree, the more complex our evaluation function will be, as crucial as the heel of Achilles.

Moreover, we try to do something different from the classic approach, even though it might not be as good as the traditional one at first. We are wondering if it is possible to use no special knowledge at all! Suppose there are two dumb playing this game without any knowledge of Gomoku except the rules. The only way for them to win is learning from their own experience. After thousands of games, they may be stronger players.

Without any Gomoku Knowledge apart from the rule, we believe an implementation using Monte Carlo algorithm can also achieve high level Gomoku AI. There are two assumptions: First, the better move will be played in most of the winning games. Second, two idiots can play the game thousands times.

First**,** we introduce Min-Max approach. **Min-Max** is a decision rule used in decision theory, game theory, statistics and philosophy for minimizing the possible loss for a worst case (maximum loss) scenario. Alternatively, it can be thought of as maximizing the minimum gain (maxmin). Originally formulated for two-player zero-sum game theory, covering both the cases where players take alternate moves and those where they make simultaneous moves, it has also been extended to more complex games and to general decision making in the presence of uncertainty.



Pic 3: a classic Min-Max Search Tree

Monte Carlo is a class of computational algorithms that rely on repeated random sampling to compute their results. Monte Carlo methods are often used in computer simulations of physical and mathematical systems. These methods are most suitable for calculation by a computer and tend to be used when it is infeasible to compute an exact result with a deterministic algorithm. This method is also used to complement theoretical derivations.

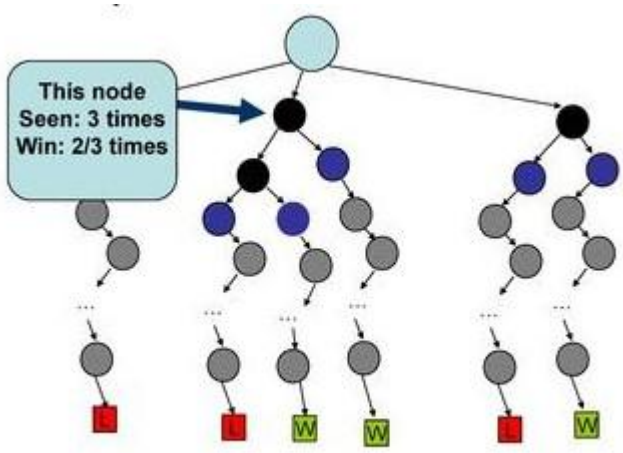
Monte Carlo Search Tree:

Here is our proposal:

(1) Moves are performed randomly with the probabilities assigned by the method of simulated annealing,

(2) The value of a position is defined by the win rate of the given position and the frequency that the move has been played

(3) To find the best move in a given position, play the game to the very end as suggested by (1) and then evaluate as in (2); play thousands of such random games, and the best move will be the one doing the best.



Pic 4: Monte Carlo Gomoku

A Dynamic Bayesian Network (DBN) is a Bayesian Network which relates variables to each other over adjacent time steps. This is often called a Two-Time slice BN because it says that at any point in time T, the value of a variable can be calculated from the internal repressors and the immediate prior value (time T-1). DBNs are common in robotics and have shown potential for a wide range of data mining applications.

Pic 5: example of a DBN.

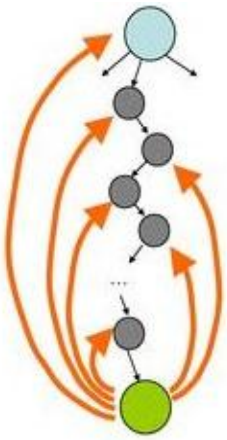
Genetic algorithm: In the computer science field of artificial intelligence, a genetic algorithm (GA) is a search heuristic simulating the process of natural evolution. This heuristic is routinely used to generate useful solutions to optimization and search problems. Genetic algorithms belong to the larger class of evolutionary algorithms (EA), which generate solutions to optimization problems using techniques inspired by natural evolution, such as inheritance, mutation, selection, and crossover.

TECHNICAL APPROACH

NAÏVE THOUGHT OF THE TWO APPROACHES

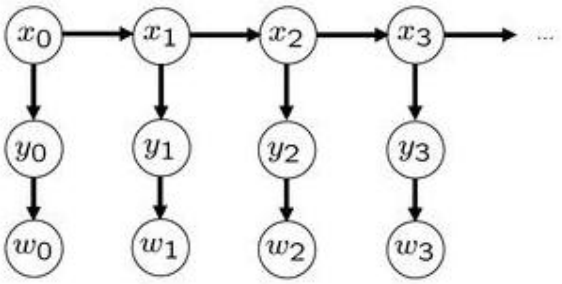
Monte Carlo Forward Approach:

(i) In each step of simulated annealing, update the values of all positions played in rollout, store the value (computed by proposal (2)) for each node.



Pic 6: update values of all positions in rollout

(ii) Given the value of the nodes, find the 5 best moves of the nodes, play them randomly, and then find the move should be performed (According to proposal (1)). Record the values of the nodes computed in (i).



Pic 7: Bayesian Network

(iii) After the opponent agent plays one move, continue Step (ii) until the end of the games.

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Min-Max:

Function integer minimax (node, depth)

If node is a terminal node or depth <= 0:

Return the Evaluation Function (node)


For child in node:                    # evaluation is identical for both players

    α = max (α, - minimax (child, depth-1))

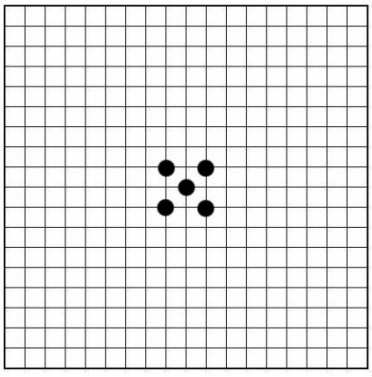
Return α
```

Min-Max Backward Approach:

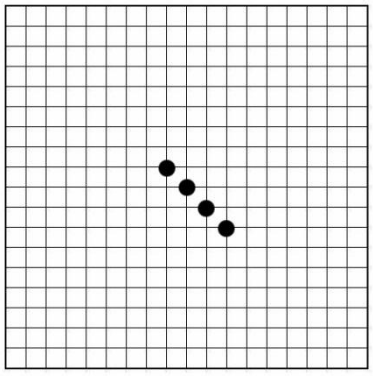
Evaluation Function: Pattern Recognition assign scores to different patterns

A move has two types of values: attack value (means playing that move can form a "good" pattern) and defense value (means playing that move can destroy opponent's "good" pattern). Then we give a definition of "good" shape. And try to assign value to each of them.

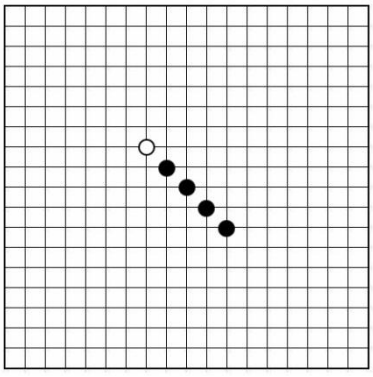
Patterns are as follow:



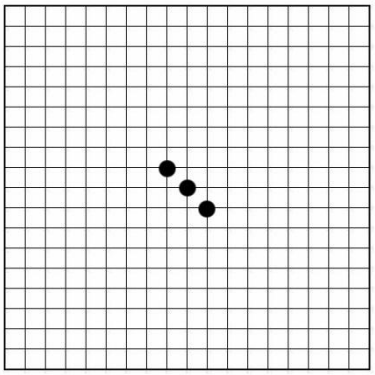
double three value() = 9970



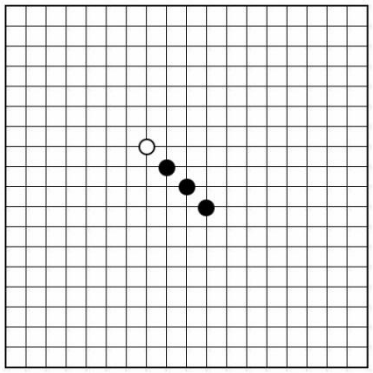
four-in-row value() = 9990



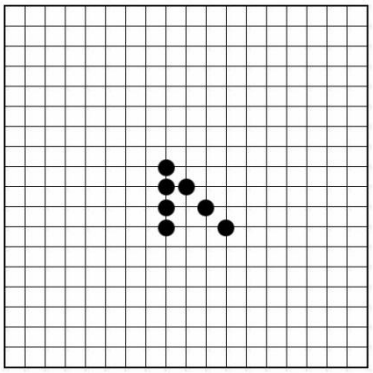
straight-four value() = 9980



three-in-row value() = 200



straight three value() = 10



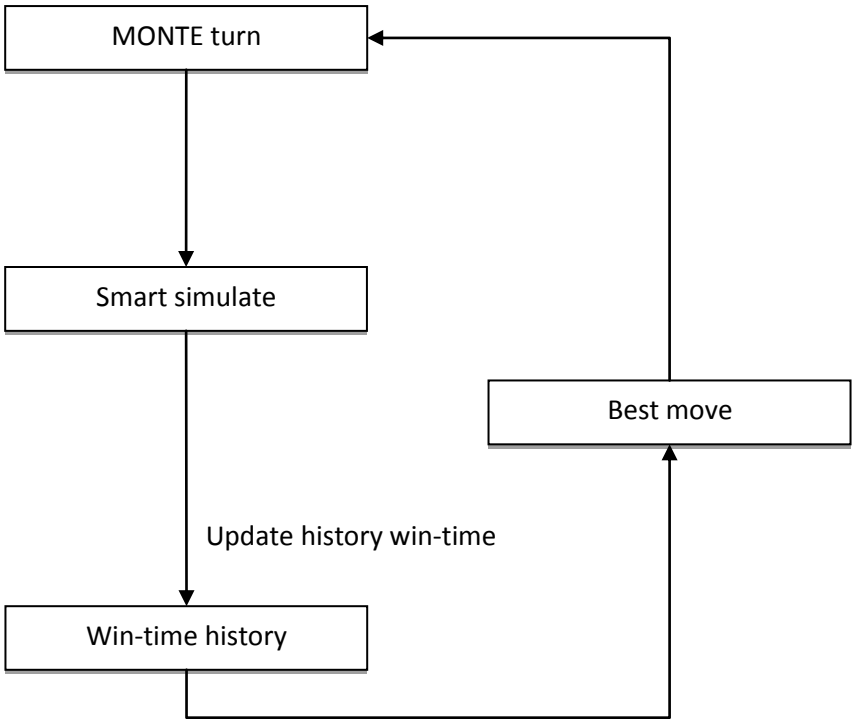
double four value() = 9998

IMPROVED ALGORIGHM

After releasing the naïve algorithm we mentioned above. We find that both of the two approaching need to be improved in order to achieve better performance and faster reaction speed.

Smart Monte Carlo Approach:

Generally speaking, the method we use in Monte Carlo Gomoku Agent is Monte Carlo Tree Search. However, we adopted some other algorithms and did several important modifications to make the agent more reasonable and intelligent.



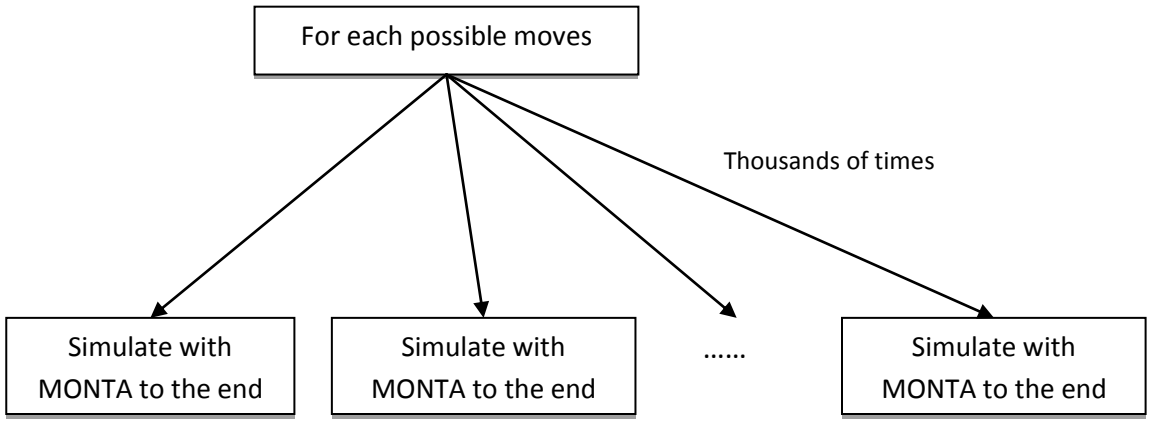
Pic 8: Monte basic process for one step(before improvement)

At the very beginning, our intuitive assumptions are:

<1>MONTE is an AI agent who only knows the rules of the Gomoku. And one day he plays that game with an expert called MiniMax. He is too weak to play with MiniMax, because different from MONTE; MiniMax knows all the best strategy of Gomoku and has a lot of experience. However, MONTE has friends help him. One is an idiot as him called MONTA (here MONTA plays randomly).

<2> (Basic: Monte plays thousands games randomly and records the result, then selects the best moves)

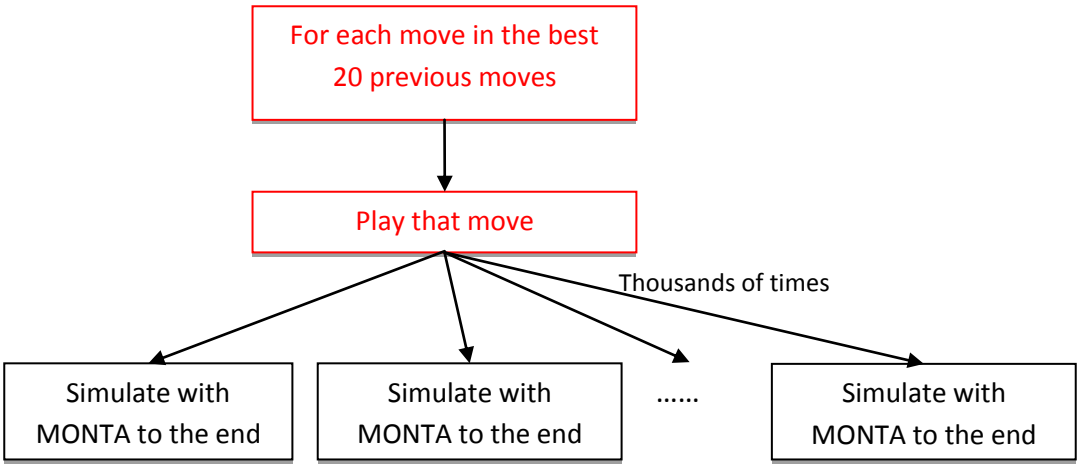
When MONTE is playing with MiniMax, MONTE and MONTA randomly try legal Gomoku moves until the game ends for thousands of times, and learn from what they have tried. There are situations that the game ends: (1) Win. (2) Lose. (3) Tie. The two play thousands times of the Gomoku game. MONTE gets "experience" based on the history win-time of every move stored in his memory. Each move is associated with a win-time. In order to do this, we updated all the win-time values of all played moves in one simulated game when one game ends. If "win", the win-time of all tried moves in this simulated game increased by 1, which is a reward; if "lost", the win-time decreased by 2, which is a punishment; if "Tie", win-time does not change. After updating the win-time, MONTE can find the move associated with highest win-time and then play it.



Pic 9: Monte's detail for the smart simulating before improvement

<3> (Improvement: Select best 20 previous moves as the initial moves and play random games, then select the best moves)

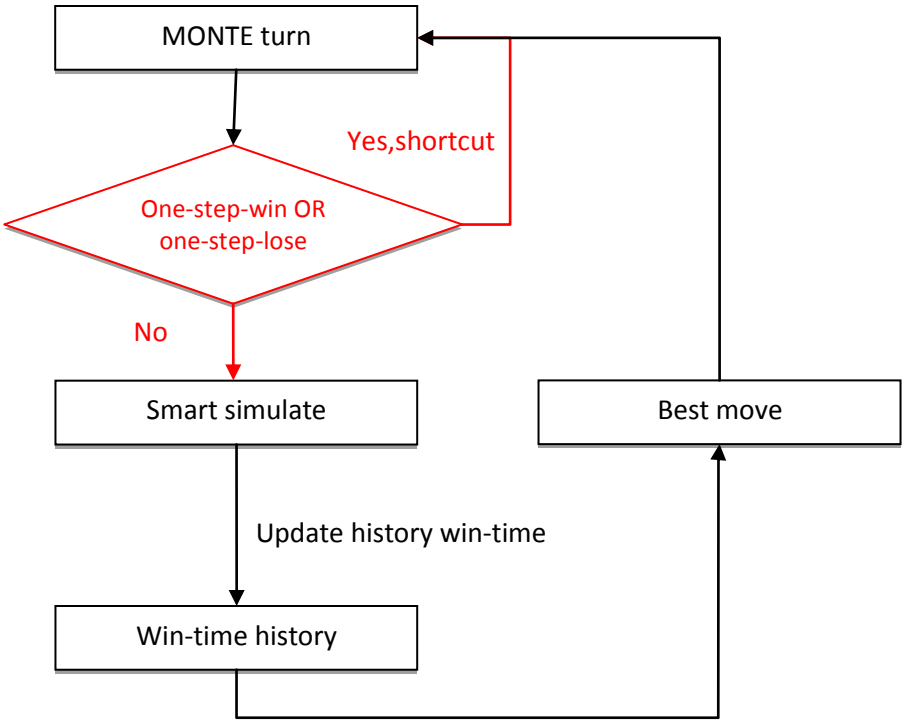
MONTE finds that not all possible moves need to play; only part of moves can be the candidates of the best moves. He tries to select best 20 previous moves as the initial moves in playing random games. These 20 moves showed their good performance in previous simulations. That gives them qualification to become the "roots". But that does not mean, after the simulating of this round, these 20 moves can still has some higher win-time value. After simulating, the rank of best moves will change, and MONTE found the “best” move (the highest win-time move) and he will play it!



Pic 10: Monte’s detail for the smart simulating after <3>

<4> (Improvement: Add short cut)

Assuming it is MONTE's turn, obviously one move will be played in this round is the move makes the MONTE wins immediately. Monte will choose that move directly without simulating as using our algorithm. Similarly, if one move will be played by the opponent makes MONTE lose immediately, Monte will choose that move directly without simulating as using our algorithm. We call this process as “Shortcut". MONTE performs like this because he knows the basic rules of the game.

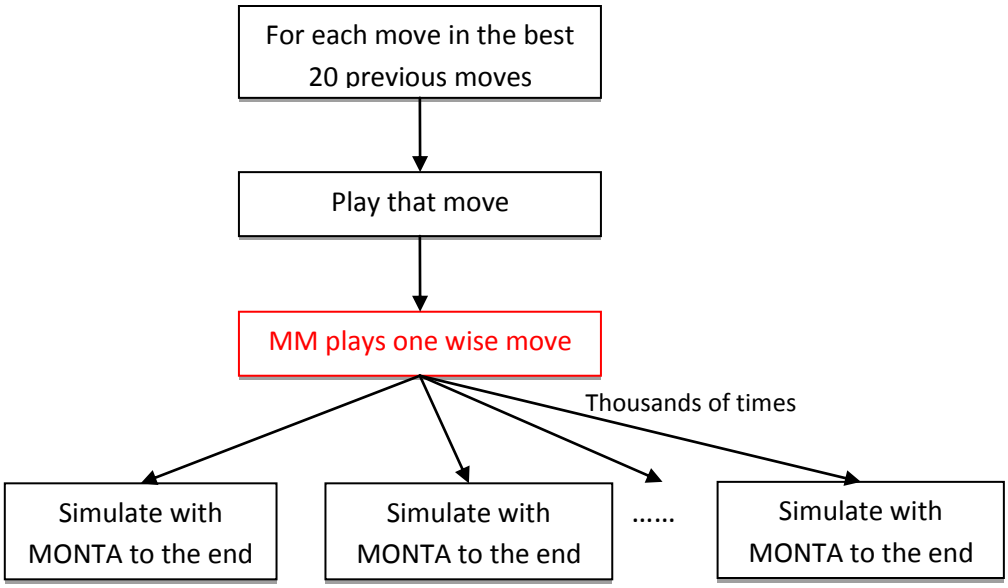


Pic 11: Monte process with short cut after <4>

<5> (Improvement: Add weak Minimax player as opponent for 1 move)

MONTE now has a new friend, MM. MM is a weaker expert who knows some of the best strategy and some experience, but his time is limited. He can only train MONTE for several steps one time. So now every step playing with MiniMax, MM will train MONTE with one next move and then MONTE has to practice with MONTA as usual.

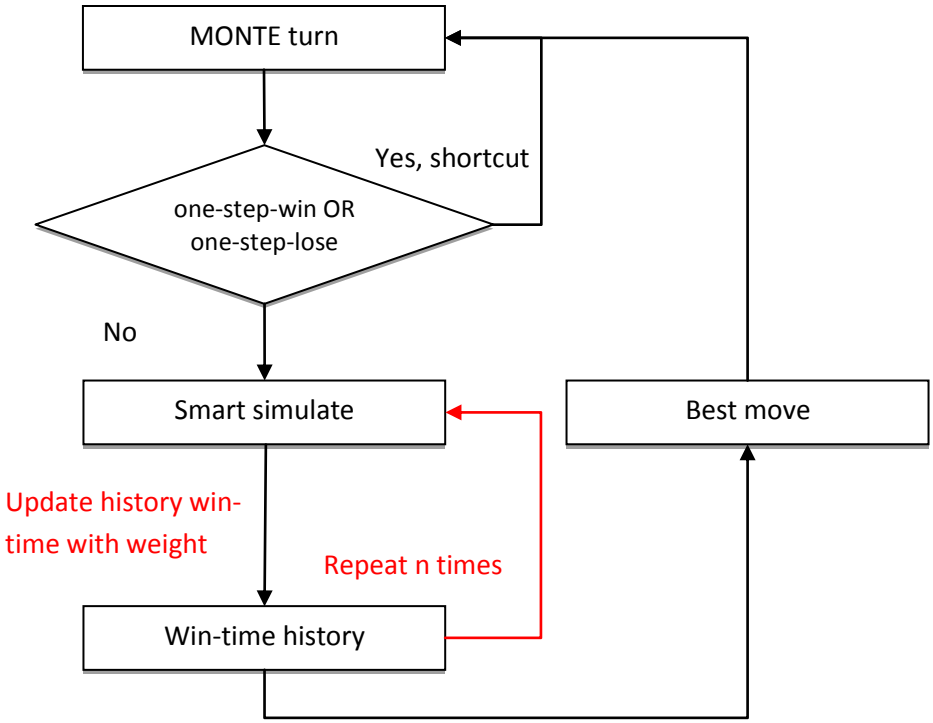
MONTE loves defending now, and previous problem like "do not know how to add one stone for an existing three stones in one line" is solved.



Pic 12: MM trained Monte's detail for the smart simulating after<5>

<6> (Improvement: Repeat smart simulating and history win-time updating for several times and add weight for current and history win-time)

After several games with Minimax, MONTE finds that in some situation the previous 20 best moves have some misleading effect, so he thinks repeating the smart simulating and history win-time updating for several times before choosing the best move may be helpful for solving misleading. Also adding some weight in updating history win-time is another good choice (new history -win-time = history-win-time* factor1 + smart–simulating-win-time*factor2). For the history win-time, its weight is smaller than the smart simulating win-time's weight, which means the history data has sort of effect, but not too much. With this change, MONTE plays much better than before.



Pic 13: Monte process after <6>

Summary:

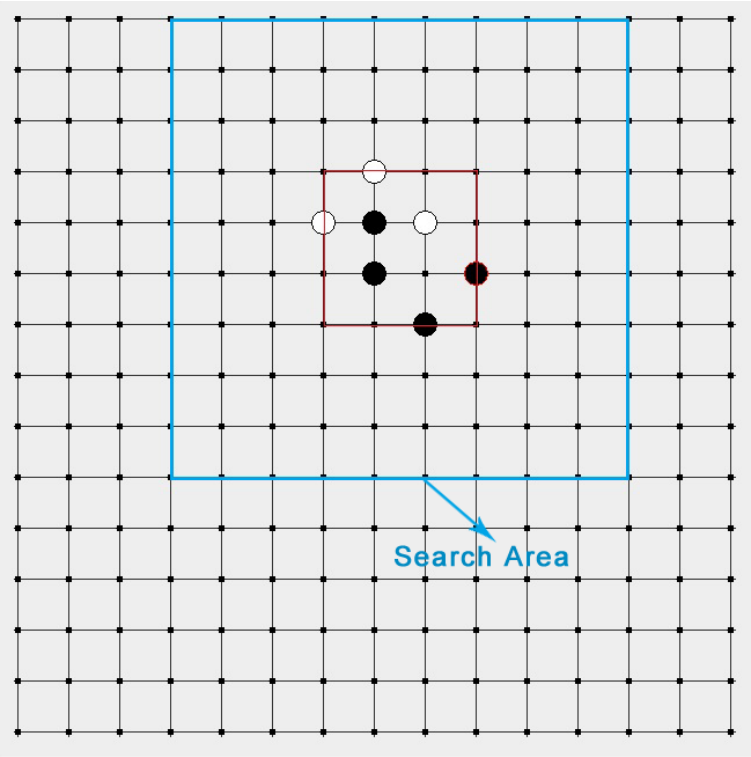
Obviously we found an OK solution for the Gomoku. It performs as well as Minimax in this case. However, Gomoku only has 15*15 possible moves in total. If we have a very large board, which means the search space is unable to travel using a complete Minimax tree, what we can do is using our new approach here, which is a combination of **Monte Carlo** and **Genetic Algorithm**, and trained by **a smaller Minimax tree**. And then we can get an approximated best solution. The thought even can be apply to all cases making decision with a search tree.

DBN is proposed as our previous model. However, the test cases show worse performance than the model we have now. The reason is, from our understanding, the limited cases we are simulating. Comparing with the whole search space 3^{225}, we only simulate at most 60,000 times, which cannot approximate the acceptable weight of every location. As a result, we keep the history win-time, and the win-time of the prior simulation will affect the entire future steps.

Also we tried different ways of simulation, which will be analyzed later with our tests results.

Fast Min-Max Approach:

The tradition approaching of the Minimax is to search all the possible moves for the next step, and build a Minimax search tree of the depth considering the whole board. Here is the Gomoku, the thing has some difference. Due the rules of this game, the best next move is always near the area where there has already been played before. Taking that character into consideration, we limited our Minimax searching area to a rectangle which is an three-intersection expansion of the smallest closure of the existing moves on each edge.



Pic 11: modified Minimax search area for certain step

SUMMARY

After this modification, the speed of our fast Minimax is doubled what we have before. Also, he can wisely make the same decision as he did before. The comparing data also will be mention in the test result.

TEST RESULT

	opponent	Win rate W:L:T (n Games)	Monte Average time per step	MiniMax Average time per step	Average step per Game
Simulating Game For Each Root Move:1000 Repeat Smart Simulating : 1 MiniMax Training Depth: 2	Minimax(3)	14:15:0(30) Win:46% Lose:50% Tie:3.33%	1.13s	5.48s	74
Simulating Game For Each Root Move:5000 Repeat Smart Simulating : 1 MiniMax Training Depth: 2	Minimax(3)	18:10:2(30) Win:60% Lose:33.33% Tie:6.67%	1.58s	5.21s	75
Simulating Game For Each Root Move:10000 Repeat Smart Simulating : 1 MiniMax Training Depth: 2	Minimax(3)	7:2:1(10) Win:70% Lose:20% Tie:10%	2.46s	5.7s	92
Simulating Game For Each Root Move:1000 Repeat Smart Simulating : 3 MiniMax Training Depth: 2	Minimax(3)	16:11:3(30) Win:53% Lose:36.37% Tie:10%	3.43s	4.67s	82
Simulating Game For Each Root Move:5000 Repeat Smart Simulating : 3 MiniMax Training Depth: 2	Minimax(3)	7:1:2(10) Win:70% Lose:10% Tie:10%	6.61s	8.57s	113
Simulating Game For Each Root Move:10000 Repeat Smart Simulating : 3 MiniMax Training Depth: 2	Minimax(3)	13:5:2(20) Win:65% Lose:25% Tie:10%	8.2s	7.7s	94
Simulating Game For Each Root move trained by Minimax(2) twice and simulates Simulating Game For Each Root Move:10000 Repeat Smart Simulating : 1 MiniMax Training Depth: 2	Minimax(3)	4:16(20) Win:20% Lose:80%	1.16s	2.2s	20

Table1: Comparison for different approaching of Monte

Test Environment: CPU Corei5, Memory 6GB

Test Argument: Win reward 1, Lose punishment 2, Tie value 0, Smart simulating win-time weight 0.6, History win-time weight 0.4

SUMMARY

In the first three lines, the MONTE plays better and better as the times of simulation increase. The more games MONTE tried means the bigger chance per location can be played. And MONTE will gain better weight of every location, like more useful experience.

Comparing line 1-3 with line 1-4, the result shows that repeating more for smart simulation increases the win rate of MONTE. That is because repeating smart simulation for several times filters the dummy best moves, which are good in the previous moves but not in this move, and the true best moves come out.

Interestingly, if we try to train him twice with MM, the Monte did worse. Why?

Suppose our win-rule is five stone in row, and generally speaking three good moves can lead one player win immediately. If the MM trains MONTE two more moves, MONTE will have a pretty low probability to win, which means he can hardly gain reward, as a result he cannot make a wise choice then. Also let us think like human beings. That training means the MONTE is a primary school student who is trained to use calculus. No surprise that he will perform worse.

	Search area	Search tree node Count for 1st step	Avg search tree node count till 5st step/step	Avg search tree node count till Game End/step
Unimproved-Minimax(3)	Whole board	1597360	1013302	642326
Improved-Minimax(3)	Limited area	73870	135515	128551

Table2: Comparison for different approaching of Minimax

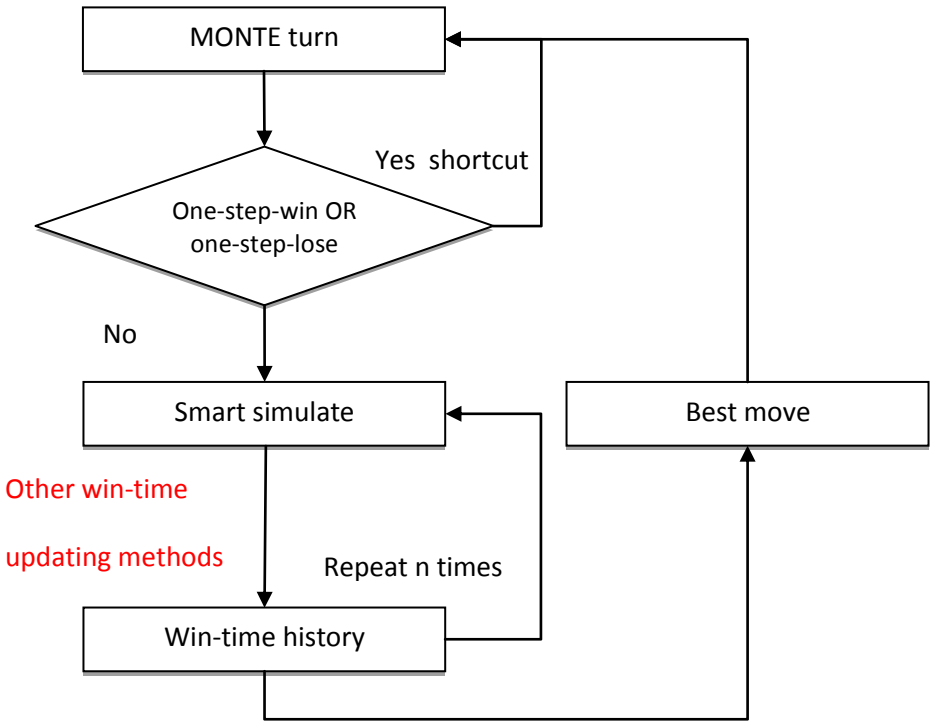
SUMMARY

Comparing the two different approaches of Minimax, at the beginning of one game, the improved Minimax performs much better than the unimproved Minimax. This is because the improved Minimax's search area is only part of the board. When the board contains more and more pieces, the improved Minimax's search area is expanded and its search tree nodes increase. This narrows the gap of the improved Minimax and unimproved Minimax. However, from the last column data, which represents the final stats of the game, the improved Minimax is still better than the unimproved one apparently.

FUTURE

In the process of our project, we have some thoughts for the further research. Because our limited time and back ground knowledge, we cannot finish it

- We find both history win-time and current simulating win-time has some effect on the current best move. Currently, we just use 0.4 as history weight and 0.6 as current weight in the Test. In the future, we want to use some other methods to calculate the new win-time list. One possible way is to map history and current win-time to [-1000, 1000] (this normalization requires deeper study on Probability Model. We tried to use equal probability model, but failed.).
- More works needed to mathematically calculate the specific time of simulation leading to the Maximum win rate.
- Also, here we use the reward 1 and punishment 2 in the win and lose cases, which is needed to be proved. Maybe other reward-punish strategy is better.



Pic 14: future Monte's process

CONCLUSION

Our proposal of this project is trying to play the Gomoku in different ways. And we achieve our original goal and find more interesting phenomenon. This project is worthy as following.

Firstly, the Gomoku is a game of our interest. It has simple rules, so that it is valuable to apply the basic algorithm and easy to find out better performance among different approaches.

Secondly, we are attempting a new solution for the game, and comparing with the classic one, which is helpful for us study deeply on the Min-Max and Monte Carlo methods.

And we successfully provide an alternative method that can deal with the situation where the search space is too large to build the whole Minimax search tree. In that case, we can use a local Minimax searching tree combining with Monte Carlo simulating. Also, further search can be done as we mentioned.

Last but not least, as Gomoku is one of the Reversi. The new attempt on Monte Carlo might benefit other board game, such as go.

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