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RESEARCH ARTICLE

An analysis of play style of advanced mahjong players toward the implementation of strong AI player

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ABSTRACT

The studies of artificial intelligence (AI) on the game with perfect information has been very much advanced to have an ability to compete top-rate human players. In contrast, it is still difficult for AI to seek the best strategy of the facing situation in the games with imperfect information. In this type of the games, it is usually more effective for a player to adopt the strategy which match the other players' strategies than to find an optimal strategy. In this study, we took mahjong as an example of complicated games with imperfect information. We propose a new method to classify opponents' strategies in mahjong by analyzing play records of mahjong called 'Haihu' statistically. We find that the advanced mahjong players' behaviors are classified into four patterns. We also validate our result by implementing simple AI programs.

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Game AI; machine Learning;
Mahjong

1. Introduction

The research on artificial intelligence (AI) for game play has a long history (10). Among them, the game with perfect information was studied exhaustively and we saw excellent progress in this area. For example, in chess, computer programs were considered to be stronger than human when Deep Blue created by IBM researchers defeated the world champion in 1997 (4). In Japanese chess which is called *Shogi*, the situation comes to be quite similar. Nowadays, many AI programs show the great ability to play compared with top ranked human players (11).

On the other hand, human player are still stronger than computer programs in the games with imperfect information such as table games (8) or video games (13). In this type of the games, it is usually very difficult to evaluate the game situation because the player can only use limited information. We think the game of *Mahjong* is especially important because it is a multi-player game with imperfect information.

The research of mahjong as a testbed of artificial intelligence has just began. There are several reasons. Of course the primary reason is that it is too difficult to tackle, but another significant reason is that it is thought as gambling, contrary to chess or go which are thought as intellectual game. Another reason is that it is not a Western game. Therefore, as you can see in the reference of this article, many of the literature are written in Japanese.

There are several researches using some learning technique for implementing a computer which plays mahjong. Chikayama uses neural network as a tool of learning (5). Komatsu proposes a Monte-carol like search method (6). However, the strength of the computer mahjong so far is not so high.

There are another type of research. It is about an analysis of human behavior in mahjong. Fortunately, there are online mahjong site and we can obtain the record of the game called 'Haifu'.



Figure 1. Examples of specific patterns of tiles. Left: Eyes, Middle: Meld (Chow), Right: Meld (Pong).



Figure 2. An examples of legal hand. This is made from one eyes and four melds.

Tosugeki-Tohoku analyzed two type of online mahjong site and presents the effective guideline for selecting good moves to win (15, 14).

We think the above two approaches should be merged in a good way. This paper does not aim to find optimal strategy for this type of game. Instead, we aim to develop a method to determine the strategy which match to the opponent strategies, because as I mentioned above, it is too difficult to find the optimum strategy, it is not so hard to find a better strategy against specific strategy. In other words, we develop the system which can estimate opponents' strategies from their behaviors. This estimation is done based on the record of the behaviors of online players.

The rest of this paper consists of the following five sections: Section 2 explains the game of mahjong and how to record players' behavior. In Section 3, we analyze the behavior of top-level player using the real game record (Haifu). In Section 4 we classify the players based on the knowledge obtained from the haifu. In Section 5, we validate our result by implementing simple artificial intelligence mahjong program. Section 6 concludes this paper.

2. The game of Mahjong

In this section, we explain what the game of mahjong is. We also explain how to record players' moves in computer readable format.

2.1. The outline

In mahjong, players use a set of 136 tiles. There are 34 kinds of tiles – three different suits (Bamboos, Characters and Circles) numbered one to nine, four Winds (East, South, West and North) and three Dragons (Red, Green and White) – and each kind of tile has four identical copies. Mahjong looks like domino because both use tiles, but rules of mahjong is similar to Western card game rummy.

In this study, we follow Japanese rule although there are many other country rules such as Chinese rule and Korean rule because mahjong is the most popular table game in Japan (9) and there are many online mahjong data available. Japanese mahjong is played with a set of mahjong tiles. A set of mahjong tiles has 136 tiles. Mahjong is commonly played by four players who compete the score. It is a game with imperfect information. Each player has 13 tiles at start. He draws one tile from the stock or discarded tiles of other players, then he discards one tile at his turn. If a player completes legal hand with 14 tiles, he can get scores.

The legal hand consists of five parts: four melds which is a specific pattern of three tiles and one eyes which is a specific pattern of two tiles. There are some exceptive legal hand which don't have any melds or eyes. The score is determined by the combination of the parts of melds and eyes. Figure 1 shows examples of eyes and melds. Figure 2 shows an example of legal hand.

A player has to pay scores when his discarded tile will be the 14th tile of the other's complete legal hand. Therefore, each player has to complete his hand, at the same time he has to estimate the opponents' hand and prevent from paying scores. Figure 3 shows the flow chart of the player behavior in mahjong.

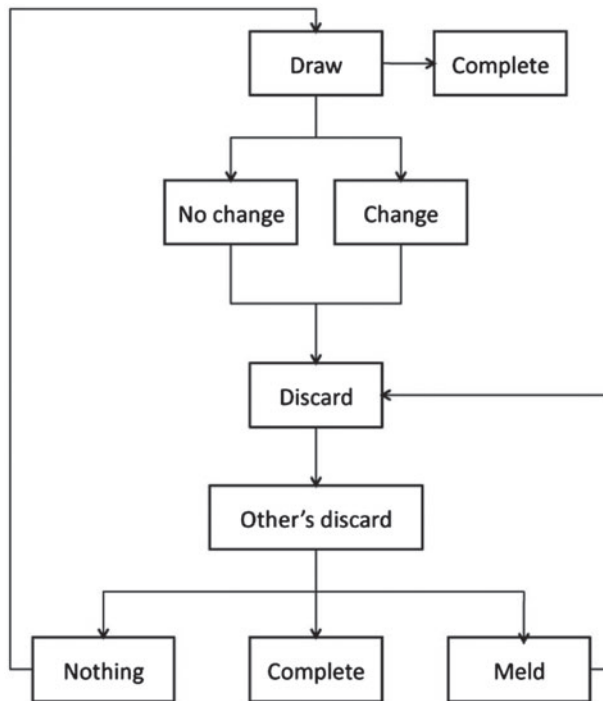


Figure 3. Action chat of a mahjong player.

2.2. Haifu – the record of the game

In mahjong, the record of all players' behavior in mahjong is called 'Haifu'. Many table game have a de facto standard notation of game records for computer program. For example, chess has PGN (Portable Game Notation) (1) and IGO has SGF (Smart Game Format) (3). But unfortunately, there are no standards of the computer-readable haifu in mahjong. In this study, we choose the Teng-ho style haifu. This haifu is written in XML based format and is transferred between the server and clients in 'Teng-ho' online mahjong site (12). Table 1 shows the definition of tags in this format. The available information from this Haifu is as follows: (1) information of games: rule type of the game, players' information, random seed, initial score of each player, initial hand of each player, information of the dealer, completed legal hands in the game and transfer of the score between players, (2) information of each player's behavior: drawn tiles, discarded tiles, melding tiles and declaration of 'Richi' (this behavior is done for getting extra score) and information of kang-Dora (this is a side effect of specific melding behavior). Figure 4 shows the example of a haifu.

3. An analysis of advanced players' behavior from Haifu

In this section, we analyze the player's behavior from haifu – the record of the game. There are many play styles in mahjong. Some are optimistic and some are pessimistic. Some are bullish and some are bearish. Thus, the players behave completely different even in the same situation. At the same time there are common behaviors among different types of players.

As an attempt to analyze the players' behaviors, we first divide the player's situation into two categories: the situation of player itself and the situation of environment. For the situation of player itself, we classify the situation in terms of tendency of completing a legal hand. For the situation of environment, we estimate how many other players are ready to complete legal hands. Then, we evaluated the action of a player.

Table 1. The definition of tags in Teng-ho style Haifu.

Tag	Meaning
<mjloggm>	Start logging
<GO ... />	Type of game
<UN ... />	Information of players
<TAIKYOKU ... />	Game start and information a dealer
<INIT ... />	Initial hands of players and the relevant information
<Txx/>, <Uxx/>, <Vxx/>, <Wxx/>	Drawn tile. T, U, V and W are position of the drawing player. Following number (xx) represents the kind of tiles
<Dxx/>, <Exx/>, <Fxx/>, <Gxx/>	Discarded tile. D, E, F and G are position of the discarding player. Following number (xx) represents the kind of tiles
<N ... >	Melding
<DORA ... />	Hidden Dora ^a
<REACH ... />	Richi and the relevant situations.
<AGARI ... />	Completed legal hands and the relevant situations
<RYUUKYOKU ... />	Game end with no winner and the relevant situations
</mjoggm>	Stop logging

^aDora is the tile which brings extra score.

Table 2. The rank of probabilities of completing a legal hand in each situation.

		Score difference from the top		
		Small	Medium	Large
Remaining dealer	0	8	9	7
	1	5	3	1
	2	2	4	6

In order to evaluate concrete situations, the haifu of the online mahjong site ‘Teng-ho’ (12) is used. We selected advanced players’ haifu of 7,888 games in Ho-Ou? table. Ho-Ou table is the place where only top-level players can enter.

3.1. Evaluation of player’s own situation

In order to evaluate a player’s own situation, we measured two numbers: (1) the remaining number of dealer in a game, and (2) the difference of score from the wealthiest player. In mahjong, each player can be a dealer twice during the game. If he is a dealer, the income is one and a half of non-dealer. Therefore, all players always have to be aware of the remaining number that he can be a dealer. The difference of score from the wealthiest player is also important. In this study, ‘Small’ difference means that the difference is less than 1,000 points. ‘Medium’ difference means that the difference is greater than 1,000 points and less than 12,600 points. ‘Large’ difference means that the difference is greater than 12,600 points.

Table 2 shows the rank of height of the probabilities of completing a legal hand calculated from the haifu data. In Table 2, the advanced players in Teng-ho are offensive when they have remaining dealer and are defensive when they have no dealer left. The most offensive situation is where they have one dealer left and the difference of score from the top player is large. Usually, this cases are turning points of the game.

3.2. Evaluation of environmental situation

As the evaluation of environmental situation of a player, we use the number of the other players whose hand is ready to complete. Of course a player can’t see the other players’ hand during the game, therefore the player has to estimate whether the other is ready to complete or not. We obtained this estimation by regression from behavior of a players which can be observed by other players.

```

<mjloggm ver="2.3">
<G0 type="169" lobby="0"/>
<UN n0="%E3%83%A4%E3%82%AD%E3%83%B3" n1="%33%33%62%6C%61%63%6B"
n2="%66%75%6B%75%30%32" n3="%E6%93%8D"
dan="17,16,17,16" rate="2148.13,2119.51,2165.11,2096.81" sx="M,F,M,M"/>
<TAIKYOKU oya="0"/>
<INIT seed="0,0,0,3,1,71" ten="250,250,250,250" oya="0"
hai0="9,55,35,2,128,80,5,38,34,72,58,60,23"
hai1="57,41,82,112,47,67,85,84,126,43,61,69,36"
hai2="26,117,79,102,40,18,39,17,22,75,114,133,53"
hai3="3,89,31,4,134,103,16,59,131,42,111,20,109"/>
<T0/>
<D128/>
<U13/>
<E126/>
<V94/>
<F114/>
<W14/>
<G131/>
... (snip) ...
<E110/>
<N who="3" m="41994"/>
<G120/>
... (snip) ...
<REACH who="1" step="1"/>
<E69/>
<REACH who="1" ten="250,240,250,250" step="2"/>
<V1/>
<F116/>
<W27/>
<G3/>
<T74/>
<D34/>
<U86/>
<N who="1" m="21504"/>
<DORA hai="123"/>
<U70/>
<E70/>
<V124/>
<F1/>
<W12/>
<AGARI ba="0,1" hai="12,14,16,20,27,59,62,65,88,89,90" m="41994"
machi="12" ten="40,12000,2" yaku="14,1,52,3,54,2" doraHai="71,123"
who="3" fromWho="3" sc="250,-60,240,-30,250,-30,250,130"/>
<INIT ...
... (snip) ...
</mjloggm>

```

Figure 4. An example of Haifu. See Table 1 for meaning of tag.

In this case, we observe how many times the player changes his tile during the game. Equation (1) shows the result of regression using the Teng-ho haifu data. Table 3 shows the information of the regression.

$$T = 0.07x_1 + 0.73x_2 + 1.32x_3 + 1.68x_4 + 1.74x_5 + 5.45 \quad (1)$$

where,

T : An anticipated number of turns when the player becomes ready to complete,

x_1 : The number of changing tile during turn 1 to turn 3,

Table 3. Statistics of the regression.

Multiple R	0.810
R square	0.653
Adjusted R square	0.653
Standard error	2.03
Observations	131,878

Table 4. Evaluation of risk of discarded tile (15).

Discarded tile of the player	Risk
4, 5, and 6 with no relation to discarded tiles of other players	12.3
4, 5, and 6 with half relation to discarded tiles of other players	7.0
3 and 7 with no relation to discarded tiles of other players	7.1
2 and 8 with no relation to discarded tiles of other players	7.0
1 and 9 with no relation to discarded tiles of other players	6.3
3, 7 with relation to discarded tiles of other players	5.5
2, 8 with relation to discarded tiles	other players 4.8
1, 9 with relation to discarded tiles other players	2.9
Winds and Dragons which can be used only for eye or meld	3.4
Winds and Dragons which can be used only for eye	0.9

- x_2 : The number of changing tile during turn 4 to turn 6,
- x_3 : The number of changing tile during turn 7 to turn 9,
- x_4 : The number of changing tile during turn 10 to turn 12,
- x_5 : The number of changing tile after turn 13.

Using this equation, we can predict the number of players who is ready to complete their hands. If the T becomes large, it means that the situation is risky.

3.3. Evaluation of player's action

The evaluation of the player's action can be calculated from the discarded tile in the player's turn. Totsugeki-Tohoku calculated the discarding risk for player who is ready to complete his hand (15). Table 4 shows the estimation for the degree of risk in discarding each type of the tiles.

For evaluating risk, the concept of 'relation' is very important. In Japanese rule of mahjong, you can't complete the hand when you discarded the tile which you need for completion of the legal hand. For example, let us consider the following situation: your hand have a set of tiles which has three meld and one eye and '3' and '4' in bamboo. In this situation, you can complete your hand If the other players discard '2' or '5' in bamboo. But if you discard the '2' or '5' before the readiness of completion, you can't complete your hand. In this case, we can say '2' has a relation to '5'. In a similar fashion, we can say '4' has a relation to '1' or '7', '6' has a relation to '3' or '9'. Therefore, the discarded tiles of the player have important information of the player's hand.

In this study, we sum up the discarding risks when multiple players are expected to be ready to complete their hand.

4. Classification of strong players in 'Teng-Ho'

In this section, we classify the play style of mahjong players using the evaluation value of the player's move in each situation. In order to do this, we first divide the situation into nine segments using the knowledge obtained in Section 3. Then we select the characteristic situations from them. Finally, we classify the players' behavior in focus of the difference of behavior in the characteristic situations.

4.1. Splitting situations for classification

We divide the situations into segments using the previous two evaluation results. One criterion of division is probabilities of completing a legal hand – condition of the players' situation. The other

Table 5. Devision of the situation based on the players condition and environmental condition.

		Probability of completing a legal hand		
		Small	Medium	Large
Number of the player ready to complete	1	s1-1	s1-2	s1-3
	2	s2-1	s2-2	s2-3
	3	s3-1	s3-2	s3-3

Table 6. Average risk of action in each situation.

		Probability of completing a legal hand		
		Small	Medium	Large
Number of the player ready to complete	1	6.56	6.57	6.55
	2	12.43	12.47	12.89
	3	21.14	21.18	21.44

Table 7. Result of principal component analysis to the behavior the advanced players. Std. Dev.: standard deviation, Prop. Var.: Proportion of variance and Cum. Prop.

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9
S1-1	0.03	0.00	-0.01	0.03	0.03	-1.00	0.06	0.01	-0.03
S1-2	0.01	0.09	0.00	0.02	0.99	0.03	-0.03	-0.03	-0.01
S1-3	0.00	0.00	0.00	0.04	0.01	-0.02	-0.01	0.00	1.00
S2-1	0.99	-0.02	-0.13	0.00	-0.01	0.03	0.00	0.00	0.00
S2-2	0.02	0.99	-0.06	0.01	-0.09	0.00	0.01	0.06	0.00
S2-3	0.00	-0.01	0.02	0.99	-0.02	0.04	0.01	0.00	-0.03
S3-1	0.13	0.05	0.99	-0.02	-0.01	0.00	0.02	0.01	0.00
S3-2	0.00	0.06	0.01	0.01	-0.04	-0.02	-0.20	-0.98	-0.01
S3-3	0.00	0.00	0.02	0.09	-0.03	-0.06	-0.97	0.20	-0.02
Std.Dev.	5.17	4.48	4.06	3.79	3.37	3.08	2.95	2.89	2.17
Prop. Var.	0.22	0.17	0.13	0.12	0.10	0.08	0.07	0.07	0.04

criterion of division is the number of the other players ready to complete – condition of environment. Then we evaluate the player's action using the risk of discarded tile. Table 5 shows how to split situations. In this study, we split the situation into 9 segments.

Table 6 shows the average risk discarded tiles.

In Table 6, the difference of situations does not affect on attitude of taking the risk. This means the behavior of top-level players is quite consistent. This result reminds us that consistent behavior is the key of success in many kinds of game and sports.

4.2. Finding characteristic situations

Table 6 shows there are no difference among the behavior of advanced players in average. However, the players act differently in real. We reveal this fact by taking a closer look at the behavior.

In the 7888 games of the haifu, 35,543 players are involved in total. We calculate the risk of the action in all nine situations for each player. So we get the data which has 35,543 points in 9-dimensional space. We classify the points (= players) using Principal Component Analysis (PCA) (2). PCA is a method to reduce the dimension of dataset with minimal loss of information. PCA realize it using orthogonal linear transformation. Table 7 shows the result of PCA of our data.

From Table 7, we can see the characteristic situations from the principal components. For example, when we see the top two principal components. Situation 2-1 has a strong correlation to PC1, Situation 2-2 has a strong correlation to PC2. Let us recall the definition of the situation. Situation 2-1 represents the situation where two other players seem to be ready to complete and the player is very offensive and Situation 2-2 represents the situation where two other players seem to be ready to complete and the player is neutral.

When we extend the range to first four principal components, all pattern of Situation 2-X (X = 1, 2, or 3) appears. This is the situation where two other players seem to be ready to complete their legal

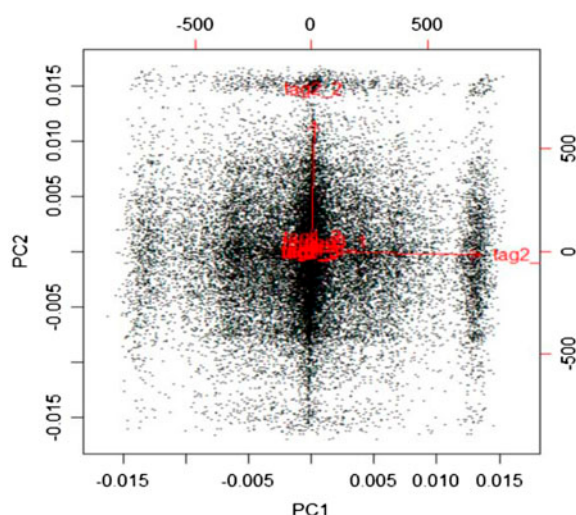


Figure 5. Biplot of the principal component analysis of player's behavior.

hand. The haifu data shows that, in these situations, the decision of advanced player has a variety. In other words, these players act homogeneously in another situation such as all three other players seem to be ready to complete or no other player seems to be ready. In former case, obviously it is good to defensive. In latter case, it is also obvious to be offensive.

4.3. Classification of the advanced players

From the result of PCA, we find that the Situation 2–1 and Situation 2–2 is the top two characteristic situation. Then we classify the advanced mahjong players' behavior in focus of the difference of their behaviors in these situations. Figure 5 shows the biplot of PCA. Biplot is a generalization of the two-variable scatter plot to represent the data and the variables in one graph. In biplot, data is displayed as points and the variables are displayed as vectors. In this case, first two principal component have only one important variable as we have seen in Section 4.2. So you can see only two long red line which represent the variables correspond to Situation 2–1 and Situation 2–2.

We can see four clusters in Figure 5: A large cluster is in the center of the figure. This cluster makes up vast majority of the players. Players in this cluster behave neutrally. Second cluster is in near the right edge of the figure. Players in this cluster behave especially offensive when they get into Situation 2–1. One small cluster is in near the upper edge of the figure. Players in this cluster behave especially offensive when they get into Situation 2–2. One more small cluster is in near the left edge of the figure. Players in this cluster behave especially defensive when they get into Situation 2–1. Interestingly, the average score of the players in these four clusters are almost the same. We will discuss this point in next section.

5. Discussion

Though the analysis behavior of advanced mahjong player in Section 4, we find that there are two types of situation: one is the situation where all players behave in the same way and the other is the situation where the players behave in different manner. Considering all the players in this haifu are placed in top-level, we can say there is one decisive move in the former situation and the players can't win without selecting these decisive moves. On the contrary, there are many acceptable moves in latter situation and the player can choose their favorite moves. We validate this interpretation using simple AI mahjong program.

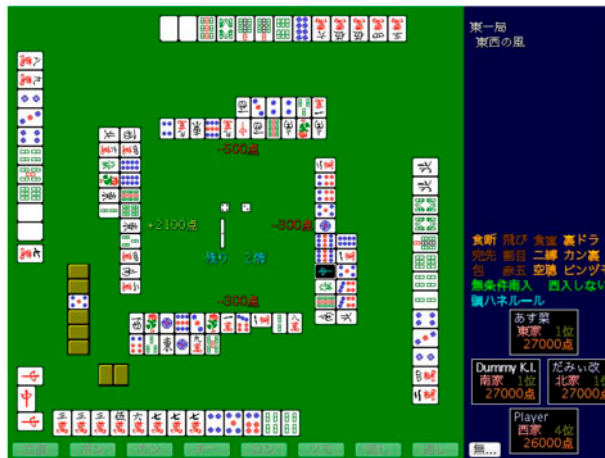


Figure 6. GUI interface of Maujong (7).

5.1. Experimental platform

We choose 'Maujong for Java' (7) as an experimental platform in this study. This is a Java based mahjong simulator made by Ishihata. It is not only the game for human, but also it supports the developing AI program. This system has several templates or concrete AI players. So users creates their own AI program just overriding the method in sample program.

For the case you would like to develop more complex program, this system provides the API (application programming interface) between the mahjong server and mahjong AI program. So the developer can concentrate on the logic. Figure 6 shows an example of execution.

In this paper, we implement the following decision making function for selecting discarded tile using the sample program:

$$S(x) = aE(h) + (1 - a)R(x) \quad (2)$$

where, $S(x)$ is the score of candidate discarded tile x , $E(h)$ is evaluation of whole hand, $R(x)$ is a risk of candidate discarded tile x and a is the parameter ($0 < a < 1$). $E(h)$ can be calculated from the melds, eyes, and doras in his hand. $R(x)$ can be calculate by Table 4.

An AI programs which implements this decision making function selects the tile x which maximize $S(x)$ as a discarded tile.

5.2. The relation between average rank of the game and the variety of actions

We split the situations into two groups: (1) Situation 2-1 and Situation 2-2, and (2) Others. This split corresponds to the result in Section 4. Then we consider the following two cases: Case (a) the AI player doesn't have a variety of action in Situation 2-1 and Situation 2-2, but have a variety of action in other situations. Case (b): the AI player have a variety of action in Situation 2-1 and Situation 2-2, but doesn't have a variety of action in other case.

Tables 8 and 9 show the average ranking of AI players. In Table 8, the lowest average rank is 2.60 and the highest average rank is 2.65. In case (a), the range of average rank is 0.05. In Table 9, on the other hand, the lowest average rank is 2.41 and the highest average rank is 3.61. In case (b), the range of average rank is 1.20. Now you can get the evidence that players' performance don't change if they change their behaviors when you are in Situation 2-1 and Situation 2-2, however, player's performance change significantly if the players change their strategy when they are in the other situations.

Table 8. The average ranking of the AI player in case (a).

α in Equation (2)	Average ranking
0.0	2.64
0.1	2.64
0.2	2.65
0.3	2.64
0.4	2.65
0.5	2.64
0.6	2.62
0.7	2.60
0.8	2.63
0.9	2.61
1.0	2.65

Table 9. The average ranking of the AI player in case (b).

α in Equation (2)	Average ranking
0.0	2.52
0.1	2.49
0.2	2.52
0.3	2.41
0.4	2.50
0.5	2.66
0.6	2.78
0.7	2.93
0.8	3.09
0.9	3.31
1.0	3.61

6. Conclusion

In this study, we tried to classify the play style of the Mahjong players from Haifu – the record of their behaviors. The players' attitude to the risk of discarding tile is used for evaluation. Analyzing the haifu of top-level players in 'Teng-Ho' online mahjong site, advanced players have the same attitude to the risk almost every situation. But there are very few situations where these players behave differently. We classified the behavior in focus of these situations by principal component analysis and find that the advanced players' behaviors are classified into one major cluster and three minor clusters. We also validate our finding using simple computer simulation. As future works, we have to consider many properties neglected in this study such as melding and richi. Then, we are planning to create AI players based on this result.

Disclosure statement

No potential conflict of interest was reported by the authors.

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