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Proposal and Evaluation of the Improved Penalty Avoiding Rational Policy Making Algorithm

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1. Introduction

Reinforcement learning (RL) is a kind of machine learning. It aims to adapt an agent to a given environment with a reward and a penalty. Traditional RL systems are mainly based on the Dynamic Programming (DP). They can get an optimum policy that maximizes an expected discounted reward in Markov Decision Processes (MDPs). We know Temporal Difference learning (Sutton, 1988) and Q-learning (Watkins, 1992) as a kind of the DP-based RL systems. They are very attractive since they are able to guarantee the optimality in MDPs. We know that Partially Observable Markov Decision Processes (POMDPs) classes are wider than MDPs. If we apply the DP-based RL systems to POMDPs, we will face some limitation. Hence, a heuristic eligibility trace is often used to treat a POMDP. We know TD(\(\lambda\)) (Sutton, 1988), Sarsa(\(\lambda\)) (Singh & Sutton, 1996), (Sutton & Barto, 1998) and Actor-Critic (Kimura & Kobayashi, 1998) as such kinds of RL systems.

The DP-based RL system aims to optimize its behavior under given reward and penalty values. However, it is difficult to design these values appropriately for the purpose of us. If we set inappropriate values, the agent may learn unexpected behavior (Miyazaki & Kobayashi, 2000). We know the Inverse Reinforcement Learning (IRL) (Ng & Russell, 2000) as a method related to the design problem of reward and penalty values. If we input an expected policy to the IRL systems, it can output a reward function that can realize just the same policy. IRL has several theoretical results, i.e. apprenticeship learning (Abbeel & Ng, 2005) and policy invariance (Ng et.al., 1999).

On the other hand, we are interested in the approach where a reward and a penalty are treated independently. As examples of RL systems that we are proposed on the basis of the viewpoint, we know the rationality theorem of Profit Sharing (PS) (Miyazaki et.al., 1994), the Rational Policy Making algorithm (RPM) (Miyazaki & Kobayashi, 1998) and PS-\(r^*\) (Miyazaki & Kobayashi, 2003). They are restricted to the environment where the number of types of a reward is one. Furthermore, we know the Penalty Avoiding Rational Policy Making algorithm (PARP) (Miyazaki & Kobayashi, 2000) and the Penalty Avoiding Profit Sharing (PAPS) (Miyazaki et.al., 2002) as examples of RL systems that are able to treat a penalty, too. We call these systems Exploitation-oriented Learning (XoL).
XoL have several features: (1) Though traditional RL systems require appropriate reward and penalty values, XoL only requires an order of importance among them. In general, it is easier than designing their values. (2) They can learn more quickly since they trace successful experiences very strongly. (3) They are not suitable for pursuing an optimum policy. The optimum policy can be acquired with multi-start method (Miyazaki & Kobayashi, 1998) but it needs to reset all memories to get a better policy. (4) They are effective on the classes beyond MDPs since they are a Bellman-free method (Sutton & Barto, 1998) that do not depend on DP.

We are interested in XoL since we require quick learning and/or learning in the class wider than MDPs. We focus on PARP and PAPS especially because they can treat a reward and a penalty at the same time. The application of PARP to a real world is difficult since it requires \( O(MN^2) \) memories where \( N \) and \( M \) are the number of types of a sensory input and an action. Though PAPS only require \( O(MN) \) memories, it may learn an irrational policy. In this paper, we aim to reduce the memories of PARP to \( O(MN) \) by updating a reward and a penalty in each episode and also selecting an action depending on the degree of a penalty. We show the effectiveness of this approach through a soccer game simulation and its real world experimentation.

2. The domain

2.1 Notations

Consider an agent in some unknown environment. For each discrete time step, after the agent senses the environment as a pair of a discrete attribute and its value, it selects an action from some discrete actions and executes it. In usual DP-based RL systems and PS, a scalar weight, that indicates the importance of a rule, is assigned to each rule. The environment provides a reward or a penalty to the agent as a result of some sequence of actions. In this paper, we focus on the class where the numbers of types of a reward and a penalty are at most ones, respectively, as same as PARP and PAPS. We give the agent a reward for achievement of our purpose and a penalty for violation of our restriction. We term the sequence of rules selected between the rewards as an episode. For example, when the agent selects \( x_b, x_a, y_a, z_a, y_b, x_a, z_a, \) and \( y_b \) in Fig. 1 a), there are two episodes \((x_b \cdot x_a \cdot y_a \cdot z_a \cdot y_b)\) and \((x_a \cdot z_a \cdot y_b)\), as shown in Fig. 1 b). Consider a part of an episode where the sensory input of the first selection rule and the sensory output of the last selection rule are the same although both rules are different. We term it as a detour. For example, an episode \((x_b \cdot x_a \cdot y_a \cdot z_a \cdot y_b)\) has two detours \((x_b)\) and \((y_a \cdot z_a)\), as shown in Fig. 1 b).

The rules on a detour may not contribute to obtain a reward. We term a rule as irrational if and only if it always exist on detours in any episodes. Otherwise, a rule is termed as rational. After obtaining the episode 1 of Fig. 1 b), rule \( x_b, y_a \) and \( z_a \) are irrational rules and rule \( x_a \) and \( y_b \) are rational rules. When the episode 2 is experienced furthermore, rule \( z_a \) changes to a rational rule. We term a rule penalty if and only if it has a penalty or it can transit to a penalty state in which there are penalty or irrational rules only.

The function that maps sensory inputs to actions is termed a policy. The policy that maximizes an expected reward per an action is termed as an optimum policy. We term a policy rational if and only if the expected reward per an action is larger than zero. We term a rational policy a penalty avoiding rational policy if and only if it has no penalty rule. Furthermore, the policy that outputs just one action for each sensory input is termed a deterministic policy.
2.2 Previous works

The Penalty Avoiding Rational Policy Making algorithm

We know the Penalty Avoiding Rational Policy Making algorithm (PARP) as XoL that can make a penalty avoiding rational policy. To avoid all penalties, PARP suppresses all penalty rules in the current rule sets with the Penalty Rule Judgment algorithm (PRJ) in Fig. 2. After suppressing all penalty rules, it aims to make a deterministic rational policy by PS, RPM and so on.

procedure The penalty Rule Judgement (PRJ)
begin
Put the mark in the rule that has been got a penalty directly

do
Put the mark in the following state;
there is no rational rule or
there is no rule that can transit to non-marked state

Put the mark in the following rule;
there are marks in the states that can be transited by it

while (there is a new mark on some state)

end

Fig. 2. The Penalty Rule Judgment algorithm (PRJ); We can regard the marked rule as a penalty rule. We can find all penalty rules in the current rule set through continuing PRJ

Furthermore, PARP avoids a penalty stochastically if there is no deterministic rational policy. It is realized by selecting the rule whose penalty level is the least in all penalty levels at the same sensory input. The penalty level is estimated by interval estimation of transition probability to a penalty state of each rule. If we can continue to select only rational rule, we can get a penalty avoiding rational policy. On the other hand, if we have to refer to the penalty level, we get a policy that has a possibility to get a penalty.

PARP uses PRJ. PRJ has to memorize all rules that have been experienced and descendant states that have been transited by their rules to find a penalty rule. It requires $O(MN^2)$ memories where $N$ and $M$ are the number of types of a sensory input and an action. Furthermore, PARP requires the same memory to suppress all penalties stochastically. In applying PRJ to large-scale problems, we are confronted with the curse of dimensionality.
The Penalty Avoiding Profit Sharing

We know PAPS as XoL to make a penalty avoiding rational policy with $O(MN)$ memories that is the same memory to storage all rules. The original PRJ requires $O(MN^2)$ memories since it scans all of the known rules. On the other hand, PAPS uses PRJ on episode (PRJ[episode]) where the scanning is restricted within each episode. Therefore it can find a penalty rule with $O(MN)$ memories.

Furthermore, PAPS uses PS[+] and PS[-] to avoid a penalty stochastically with $O(MN)$ memories. PS[+] is the same as PS whose weights are reinforced only by a reward. It is used in the case where there is a non-penalty rule in a current state. If there is no non-penalty rule in a current state, PAPS selects an action that is the least reinforced by PS[-] whose weights are reinforced by a penalty only.

PAPS aims to make a penalty avoiding rational policy with $O(MN)$ memories. However there is a serious problem in the action selection based on PS[-]. Originally, PS aims to learn a rational policy that reaches to a reward. In the same way, we can get a policy that reaches to a penalty, if we select an action that is the most reinforced by PS[-] in each state. However, we cannot know how rules except for the most reinforced rule are reinforced. Therefore we may select an action that will get a penalty with rather high possibility, even if we select the least reinforced rule in the current state.

3. Improvement of the penalty avoiding rational policy making algorithm

3.1 Basic ideas

We aim to make a penalty avoiding rational policy with $O(MN)$ memories. A penalty rule is found by PRJ[episode] as well as PAPS. Therefore, we can find a penalty rule with $O(MN)$ memories.

If we cannot select any non-penalty rules in a current state, we should avoid a penalty stochastically. It is realize with penalty level of each rule as PARP. PARP has to memorize all state transitions in order to calculate the penalty level. It means that it requires $O(MN^2)$ memories. In order to reduce the memory to $O(MN)$, we aim to calculate the penalty level by each episode.

3.2 Approximation of the penalty level

We do not memorize all state transitions but memorize only state transitions of each episode to estimate the penalty level of each rule. It only requires $O(MN)$ memories. The penalty level of rule $S_1a$, $PL(S_1a)$, is calculated by the following equation:

$$PL(S_1a) = \frac{N_p(S_1a)}{N(S_1a)}$$

(1)

where $N_p(S_1a)$ is the number of times that rule $S_1a$ has judged as a penalty rule, and $N(S_1a)$ is the number of times that the rule has been selected so far. We show examples of $N_p(S_1a)$ and $N(S_1a)$ at a rectangle of Fig. 3 (b) and ellipses of Fig. 3 (a)(b), respectively.

The range of $PL(S_1a)$ is $1.0 \geq PL(S_1a) \geq 0.0$. If $PL(S_1a)$ is close to 1.0, we can regard that the possibility of getting a penalty by the action $a$ in the state $S_1$ is high. On the other hand, if $PL(S_1a)$ is close to 0.0, we can regard that the possibility is low. We can calculate $PL(S_1a)$ every episodes. It requires the following two types memories only. One is the number of
times where each rule has been selected until now. The other is that where each rule has been judged to a penalty rule. They only require \(O(MN)\) memories.

Fig. 3. Approximation of the penalty level

### 3.3 The action selection based on the penalty level

If there is a rational rule in the current rule set after excluding all penalty rules, we should select the rule to make a penalty avoiding rational policy. It is realized by \(PS(PS[+])\) or RPM. On the other hand, if we cannot select such rule, we select an action in the rule whose penalty level calculated by equation (1) is the least in order to reduce the probability of getting a penalty.

From section 2.1, the rule that has a possibility to get a penalty is defined as a penalty rule. This definition has a possibility of regarding all rules as penalty rules. We introduce the cutting parameter \(\gamma\) \((1.0 \geq \gamma \geq 0.0)\) to reduce the number of penalty rules. If \(PL(S_{at})\) is larger than \(\gamma\), the rule \(S_{at}\) is a penalty rule. Otherwise, it is not a penalty rule. It means that the rule is not regarded as a penalty rule if the possibility of getting a penalty is low. If we set \(\gamma=0.0\), the rule that has been given a penalty even once is regarded a penalty rule. It is coincident to the case where we do not introduce the parameter \(\gamma\) to PARP. On the other hand, if \(\gamma\) is closed to 1.0, the number of penalty rules will decrease, and in turn, the number of rules that can be selected by \(PS(PS[+])\) or RPM will increase significantly. If we set \(\gamma=1.0\), it is coincident to \(PS(PS[+])\) or RPM that do not avoid any penalty. We can control the number of rules that can be selected with \(\gamma\).

### 3.4 Features

We call the proposal method *Improved PARP*. Improved PARP has the following features.
- We can avoid a penalty stochastically with $O(MN)$ memories through combining of both PRJ[episode] and the approximation of a penalty level.
- We can control the number of penalty rules with the cutting parameter $\gamma$.

4. Numerical experimentation

We use the simulator shown in Fig. 4 that is based on the Small Size Robot League on RoboCup. There are two learning agents for one side. One agent puts a pass out for the other agent. The other agent aims to receive it. There is an opponent agent for the other side. The agent aims to cut off the pass. We show the initial positions of these agents in Fig. 4. We know the keepaway task (Stone et.al. 2005) as another soccer game. The performance of the keepaway task strongly depends on the designing of a reward and a penalty (Tanaka & Arai, 2006). In the future, we will challenge to the keepaway task, too.

![Fig. 4. Soccer game simulator](image)

4.1 Detail design of the task

The learning agents

The state spaces of a learning agent is classified to the following five cases; 9 states of a ball from the learning agent (Fig. 5 a)), 10 states of an opponent agent from the learning agent (Fig. 5 b)), 5 states of the other learning agent from the learning agent (Fig. 5 c)), 4 states of destination between two learning agents (Fig. 5 d)) and 5 states of the learning agent from the other learning agent (Fig. 5 c)).

There are the following seven actions; stop, go forward, turn by five degrees to direction of a ball, turn right by five degrees, turn left by five degrees, kick for dribble and kick for pass.
A reward and a penalty

The learning is judged to success when a ball in a learning agent had reached to the other learning agent and the distance between two learning agents is larger than 40cm. A reward is given to two learning agents when the condition for success is achieved. A penalty is given to two learning agents when a ball had reached to an opponent agent, the learning time had exceeded 12000 msec that is called Timeout, or a ball in a learning agent had reached to the other learning agent but the distance between two learning agents is not larger than 40cm. Though there are three types of penalties, learning agents do not distinguish them, that is, they are treated as the same penalty. In the future, we will try to the case where these penalties are treated independently.

The opponent agent

There are two policies in the opponent agent. One policy aims to reach to a ball. The other policy aims to reach to the middle position of two learning agents to block the pass. The former is selected when the distance from the agent to a ball is closer than the distance from the agent to the middle position of two learning agents. Otherwise, the latter policy is selected.
Setting of the experiment
The learning agents sense the environment each 3 msec. When they had received a reward or a penalty, the trial has been ended and new trial begins with the initial position. We take 100 experiments with different random seeds.
We introduce two noises to simulate a stochastic state transition. One is added to the movements of all agents and a ball. The maximum value is \( \pm 1/10 \text{[mm/s]} \). The other is added to the angles of the turn actions of learning agents and the direction of a ball when agents kicked it. The maximum value is \( \pm 1/100 \text{[deg]} \).

4.2 Results and discussion
About the setting of \( \gamma \)
We have compared our proposed method called Improved PARP with PAPS. On the other hand, PARP cannot apply to this task since it requires many memories. We have changed \( \gamma \) every 0.1 from 0.5 up to 1.0. Fig. 6 and Fig. 7 are the results of success rates of pass behaviors of PAPS and Improved PARP, respectively. The horizontal axis is the number of trials and the vertical axis is the percentage of the success rate. One trial includes a pair of sensing the environment and selecting an action. The plots are shown every 100 trials. The initial point of these plots are the results of random walk.
Fig. 6 shows that PAPS cannot learn. It comes from the fact that the penalty avoiding by \( \text{PS[-]} \) does not function properly. On the other hand, we can conclude that Improved PARP gets high performance than PAPS from these figures.

![Fig. 6. Success rate (%) of pass behavior by PAPS](image)

If we decrease \( \gamma \), the number of penalty rules of Improved PARP increases. It means that the penalty avoiding is more important than the reward getting. Therefore, if we decrease \( \gamma \), the
action selection based on PS(PS[+]) decreases, and the success rates become bad as shown in Fig. 7. On the other hand, if we increase $\gamma$ until 0.8, the success rates become good. It comes from the fact that the action selection based on PS(PS[+]) increases because of decreasing the number of penalty rules. However, the results of $\gamma$=0.9 and 1.0 show bad. It means that if we set $\gamma$ excessively largely, the learning agents regard an important penalty rule as a non-penalty rule.

The result of Improved PARP depends on $\gamma$. If we set $\gamma$ small, we can get a policy that is focused on a penalty avoiding. If we set $\gamma$ large, we can get a policy that is focused on a reward getting. Therefore, we should change $\gamma$ dynamically. For example, we should set $\gamma$ large to get a goal in the initial phase of a game or in the situation where the game may lose. On the other hand, we should set $\gamma$ small to protect our goal when our score being more than the other.

About the setting of penalties
We give a learning agent the same penalty when the learning reaches TimeOut, a ball had reached to an opponent agent, or a ball in a learning agent had reached to the other learning agent but the distance between two learning agents is not larger than 40cm. We confirm the effects of first two penalties. Fig. 8 shows the TimeOut rate plotted against the number of trials. Fig. 9 shows miss rate of pass behavior plotted against the number of trials. Though we can confirm the effect of learning in Fig. 8, we cannot do it in Fig. 9. It comes from the fact that the policy that is specialized in TimeOut has been learned than the other policies, since TimeOut occurs frequently than the others. Therefore, we should not give the same penalty to the different types of behaviors. In the future, we aim to combine Improved
PARP with the method in the paper (Miyazaki & Kobayashi, 2004) that can treat several types of rewards and penalties at the same time.

Fig. 8. Timeout rate (%) by Improved PARP

Fig. 9. Miss rate of pass behavior by Improved PARP
5. Real world experimentation

5.1 The soccer robot system

We have developed a soccer robot system (Fig. 10) to evaluate improved PARP. It has the decision making subsystem and the image processing subsystem. The former is to decide an action and the latter is to process images from camera. It can adapt on the reguration of Robo Cup Small Size Robot League except for the field size.

5.2 Soccer robot

We use three robots called Robo-E (Fig. 11). It has 12 light sensors. They are used to escape from clashing with a wall or another robots. Each robot has different markers each other to distinguish each robot. We show the combinations of colors for robots in table.1.
5.3 Host system

The host system is constructed by two computers, that is, Host and Image Processing (IP) PCs. IP and Host PCs are connected by TCP/IP. We use UDP (User Datagram Protocol) as the protocol on IP.

Host PC is to decide an action. We have implemented Improved PARP on Host PC. The decision of Host PC is transmitted by wireless modem.

On the other hand, IP PC is to process images from camera. It calculates positions of robots and a ball. Their images are given by the camera (SONY XC-003; Fig. 12). We had the camera mounted at the top of the field to get global vision. We use machine vision tool HALCON with its Hdevelop programming environment to get robots and a ball positions. The positions of each robot are calculated with markers on Table. 1 and their body color (black). We use RGB parameter to distinguish each color. Table 2 shows these thresholds.

<table>
<thead>
<tr>
<th>Color</th>
<th>R</th>
<th>G</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>Field (green)</td>
<td>10-40</td>
<td>75-100</td>
<td>40-65</td>
</tr>
<tr>
<td>Robot (black)</td>
<td>0-20</td>
<td>0-55</td>
<td>0-220</td>
</tr>
<tr>
<td>Wall (white)</td>
<td>255</td>
<td>255</td>
<td>255</td>
</tr>
<tr>
<td>Ball (orange)</td>
<td>125-200</td>
<td>95-125</td>
<td>45-85</td>
</tr>
<tr>
<td>Yellow</td>
<td>170-255</td>
<td>180-255</td>
<td>110-190</td>
</tr>
<tr>
<td>Blue</td>
<td>30-110</td>
<td>40-30</td>
<td>80-200</td>
</tr>
<tr>
<td>Light green</td>
<td>40-130</td>
<td>130-230</td>
<td>60-180</td>
</tr>
<tr>
<td>Cyan</td>
<td>100-170</td>
<td>140-240</td>
<td>140-240</td>
</tr>
</tbody>
</table>

Table 2. RGB parameter of each color
The position of the robot is the center of gravity of two markers. It is \((X_{\text{robot}}, Y_{\text{robot}})\) on Fig. 13 (a). The position of a ball is the center of ball marker (orange). It is \((X_{\text{ball}}, Y_{\text{ball}})\) on Fig. 13 (b).

Fig. 13. Positions of robots and a ball

The orientation of the robot is calculated by the center of gravity of two markers (Fig. 14). If we set the center of gravity of center marker \((X_{\text{center}}, Y_{\text{center}})\) and it of another marker \((X_{\text{outside}}, Y_{\text{outside}})\), we can get the angle \(\theta\) is as the following,

\[
\theta = \text{atan2}(d_y, d_x), \quad \text{\((180^\circ < \theta < 180^\circ)\)}
\]

(2)

where \(d_x, d_y\) is \(d_x = x_{\text{outside}} - x_{\text{center}}, d_y = y_{\text{outside}} - y_{\text{center}}\).

Fig. 14. Orientation of a robot

5.4 Experimental results
We use three Robo-E type robots in our real world experimentation. One is an opponent agent and the others are learning agents. Three robots and a ball are set on the field in Fig. 15.
Fig. 15. Real world field

Fig. 16 shows the results of success rates of pass behavior of Improved PARP, the Q-learning and random agents. Improved PARP has 4 experiments with different random seeds from SEED_1 to SEED_4. We set $\gamma=0.8$. We can confirm the effectiveness of Improved PARP as same as numerical experimentation. Especially, it can learn very quickly than Q-learning agent that is the most famous DP-based RL system.

Fig. 16. Success rate (%) of pass behavior in real world experimentation
6. Conclusion

As examples of XoL that use both a reward and a penalty simultaneously, we know PARP and PAPS. The application of PARP to real worlds is difficult since it requires $O(MN^2)$ memories where $N$ and $M$ are the number of types of a sensory input and an action. Though PAPS only requires $O(MN)$ memories, it may learn unexpected behavior.

In this paper, we have proposed **Improved PARP** in order to overcome the difficulty by updating a reward and a penalty in each episode and selecting actions depending on the degree of a penalty. We have shown the effectiveness of this approach through a soccer game simulation and its real world experimentation.

Improved PARP cannot treat multiple rewards and penalties. In the future, we try to combine Improved PARP with the method in the paper (Miyazaki & Kobayashi, 2004) to treat several types of rewards and penalties at the same time. Furthermore, we will apply Improved PARP to the *keepaway task* (Stone et.al. 2005) and the other real world applications.

7. References


Even since computers were invented, many researchers have been trying to understand how human beings learn and many interesting paradigms and approaches towards emulating human learning abilities have been proposed. The ability of learning is one of the central features of human intelligence, which makes it an important ingredient in both traditional Artificial Intelligence (AI) and emerging Cognitive Science. Machine Learning (ML) draws upon ideas from a diverse set of disciplines, including AI, Probability and Statistics, Computational Complexity, Information Theory, Psychology and Neurobiology, Control Theory and Philosophy. ML involves broad topics including Fuzzy Logic, Neural Networks (NNs), Evolutionary Algorithms (EAs), Probability and Statistics, Decision Trees, etc. Real-world applications of ML are widespread such as Pattern Recognition, Data Mining, Gaming, Bio-science, Telecommunications, Control and Robotics applications. This book reports the latest developments and futuristic trends in ML.

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