Learning Credit Assignment for Cooperative Multi-Agent Reinforcement Learning (IJCAI 21)

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Abstract
Cooperative multi-agent policy gradient (MAPG) algorithms have recently attracted wide attention and are regarded as a general scheme for the multi-agent system. Credit assignment plays an important role in MAPG and can induce cooperation among multiple agents. However, most MAPG algorithms cannot achieve good credit assignment because of the game-theoretic pathology known as centralized-decentralized mismatch. To address this issue, this paper presents a novel method, Multi-Agent Polarization Policy Gradient (MAPPG). MAPPG takes a simple but efficient polarization function to transform the optimal consistency of joint and individual actions into easily realized constraints, thus enabling efficient credit assignment in MAPG. Theoretically, we prove that individual policies of MAPPG can converge to the global optimum. Empirically, we evaluate MAPPG on the well-known matrix game and differential game, and verify that MAPPG can converge to the global optimum for both discrete and continuous action spaces. We also evaluate MAPPG on a set of StarCraft II micromanagement tasks and demonstrate that MAPPG outperforms the state-of-the-art MAPG algorithms.

1 Introduction
Multi-agent reinforcement learning (MARL) is a critical learning technology to solve sequential decision problems with multiple agents. Recent developments in MARL have heightened the need for fully cooperative MARL that maximizes a reward shared by all agents. Cooperative MARL has made remarkable advances in many domains, including autonomous driving [Cao et al., 2021] and cooperative transport [Shibata et al., 2021]. To mitigate the combinatorial nature [Hernandez-Leal et al., 2019] and partial observability [Omidshafiei et al., 2017] in MARL, centralized training with decentralized execution (CTDE) [Oliehoek et al., 2008; Kraemer and Banerjee, 2016] has become one of the mainstream settings for MARL, where global information is provided to promote collaboration in the training phase and learned policies are executed only based on local observations.

Multi-agent credit assignment is a crucial challenge in the MARL under the CTDE setting, which refers to attributing a global environmental reward to the individual agents’ actions [Zhou et al., 2020]. Multiple independent agents can learn effective collaboration policies to accomplish challenging tasks with the proper credit assignment. MARL algorithms can be divided into value-based and policy-based. Cooperative multi-agent policy gradient (MAPG) algorithms can handle both discrete and continuous action spaces, which is the focus of our study. Different MAPG algorithms adopt different credit assignment paradigms, which can be divided into implicit and explicit credit assignment [Zhou et al., 2020]. Solving the credit assignment problem implicitly needs to represent the joint action value as a function of individual policies [Lowe et al., 2017; Zhou et al., 2020; Wang et al., 2021b; Zhang et al., 2021; Peng et al., 2021]. Current state-of-the-art MAPG algorithms [Wang et al., 2021b; Zhang et al., 2021; Peng et al., 2021] impose a monotonic constraint between the joint action value and individual policies. While some algorithms allow more expressive value function classes, the capacity of the value mixing network is still limited by the monotonic constraints [Son et al., 2019; Wang et al., 2021a]. The other algorithms that achieve explicit credit assignment mainly provide a shaped reward for each individual agent’s action [Proper and Tumer, 2012; Foerster et al., 2018; Su et al., 2021]. However, there is a large discrepancy between the performance of algorithms with explicit credit assignment and algorithms with implicit credit assignment.

In this paper, we analyze this discrepancy and pinpoint that the centralized-decentralized mismatch hinders the performance of MAPG algorithms with explicit credit assignment. The centralized-decentralized mismatch can arise when the sub-optimal policies of agents could negatively affect the assessment of other agents’ actions, which leads to catastrophic miscoordination. Note that the issue of centralized-decentralized mismatch was raised by DOP [Wang et al., 2021b]. However, the linearly decomposed critic adopted by DOP limits their representation expressiveness for the value function.

Inspired by Polarized-VAE [Balasubramanian et al., 2021] and Weighted QMIX [Rashid et al., 2020], we propose a policy-based algorithm called Multi-Agent Polarization
**Policy Gradient** (MAPPG) for learning explicit credit assignment to address the *centralized-decentralized mismatch*. MAPPG encourages increasing the distance between the global optimal joint action value and the non-optimal joint action values while shortening the distance between multiple non-optimal joint action values via polarization policy gradient. MAPPG facilitates large-scale multi-agent cooperations and presents a new multi-agent credit assignment paradigm, enabling multi-agent policy learning like single-agent policy learning. Theoretically, we prove that individual policies of MAPPG can converge to the global optimum. Empirically, we verify that MAPPG can converge to the global optimum compared to existing MAPG algorithms in the well-known StarCraft II unit micromanagement tasks [Samvelyan et al., 2019], demonstrating its scalability in complex scenarios. Finally, the results of ablation experiments match our theoretical predictions.

2 Related Work

2.1 Implicit Credit Assignment

In general, implicit MAPG algorithms utilize the learned function between the individual policies and the joint action values for credit assignment. MADDPG [Lowe et al., 2017] and LICA [Zhou et al., 2020] learn the individual policies by directly ascending the approximate joint action value gradients. The state-of-the-art MAPG algorithms [Wang et al., 2021b; Zhang et al., 2021; Peng et al., 2021; Su et al., 2021] introduce the idea of value function decomposition [Sunehag et al., 2018; Rashid et al., 2018; Son et al., 2019; Wang et al., 2021a; Rashid et al., 2020] into the multi-agent actor-critic framework. DOP [Wang et al., 2021b] decomposes the centralized critic as a weighted linear summation of individual critics that condition local actions. FOP [Zhang et al., 2021] imposes a multiplicative form between the optimal joint policy and the individual optimal policy, and optimizes both policies based on maximum entropy reinforcement learning objectives. FACMAC [Peng et al., 2021] proposes a new credit-assignment actor-critic framework that factors the joint action value into individual action values and uses the centralized gradient estimator for credit assignment. VDAC [Su et al., 2021] achieves the credit assignment by enforcing the monotonic relationship between the joint action values and the shaped individual action values. Although these algorithms allow more expressive value function classes, the capacity of the value mixing network is still limited by the monotonic constraints, and this claim will be verified in our experiments.

2.2 Explicit Credit Assignment

In contrast to the implicit algorithms, explicit MAPG algorithms provide the contribution of each individual agent’s action, and individual actors are updated by following policy gradients tailored by the contribution. COMA [Foerster et al., 2018] evaluates the contribution of individual agents’ actions by using the centralized critic to compute an agent-specific advantage function. SQDDPG [Wang et al., 2020] proposes a local reward algorithm, Shapley Q-value, which takes the expectation of marginal contributions of all possible coalitions. Although explicit algorithms provide valuable insights into the assessment of the contribution of individual agents’ actions to the global reward and thus can significantly facilitate policy optimization, the issue of *centralized-decentralized mismatch* hinders their performance in complex scenarios. Compared to these explicit algorithms, the proposed MAPPG can theoretically tackle the challenge of *centralized-decentralized mismatch* and experimentally outperforms existing MAPG algorithms in both convergence speed and final performance in challenging environments.

3 Background

3.1 Dec-POMDP

A decentralized partially observable Markov decision process (Dec-POMDP) is a tuple \( \langle S, U, r, P, Z, O, n, \gamma \rangle \), where \( n \) agents identified by \( a \in A = \{1, \ldots, n\} \) choose sequential actions, \( s \in S \) is the state. At each time step, each agent chooses an action \( a \in U \), forming a joint action \( u \in U^n \) which induces a transition in the environment according to the state transition function \( P(s' | s, u) : S \times U \times S \rightarrow [0, 1] \). Agents receive the same reward according to the reward function \( r(s, u) : S \times U \rightarrow \mathbb{R} \). Each agent has an observation function \( O(s, a) : S \times A \rightarrow Z \), where a partial observation \( z_a \in Z \) is drawn. \( \gamma \in [0, 1) \) is the discount factor. Throughout this paper, we denote joint quantities over agents in bold, quantities with the subscript \( a \) denote quantities over agent \( a \), and joint quantities over agents other than a given agent \( a \) with the subscript \( -a \). Each agent tries to learn a stochastic policy for action selection: \( \pi_a : T \times U \rightarrow [0, 1] \), where \( \tau_a \in T \equiv (Z \times U)^n \) is an action-observation history for agent \( a \). MARL agents try to maximize the discounted return, \( R_t = \sum_{i=1}^{\infty} \gamma^{t-i-1}r^t \), where \( r^t \) is the reward obtained from the environment by all agents at step \( t \).

3.2 Multi-Agent Policy Gradient

We first provide the background on single-agent policy gradient algorithms, and then introduce multi-agent policy gradient algorithms. In single-agent tasks, policy gradient algorithms [Sutton et al., 1999] optimise a single agent’s policy, parameterised by \( \theta \), by performing gradient ascent on an estimator of the expected discounted total reward \( \nabla_\theta J(\pi) = \mathbb{E}_\pi [\nabla_\theta \log \pi (u | s) R^0] \), where the gradient is estimated from trajectories sampled from the environment. Actor-critic [Sutton et al., 1999; Konda and Tsitsiklis, 1999; Schulman et al., 2016] algorithms use an estimated action value instead of the discounted return to solve the high variance caused by the likelihood-ratio trick in the above formula. The gradient of the policy for a single-agent setting can be defined as:

\[
\nabla_\theta J(\pi) = \mathbb{E}_\pi [\nabla_\theta \log \pi (u | s) Q(s, u)].
\]

A natural extension to multi-agent settings leads to the multi-agent stochastic policy gradient theorem with agent \( a \)’s policy parameterized by \( \theta_a \) [Foerster et al., 2018; Wei et al., 2018],
shown below:

\[
\nabla_\theta J (\pi) = E_\pi \left[ \sum_a \nabla_\theta \log \pi_a (u_a | \tau_a) Q (s, u) \right] = \sum_s d^\pi (s) \sum_a \pi_a (u_a | \tau_a) \nabla_\theta \log \pi_a (u_a | \tau_a) \sum_{u_{-a}} \pi_{-a} (u_{-a} | \tau_{-a}) Q (s, u). \tag{2}
\]

where \(d^\pi (s)\) is a discounted weighting of states encountered starting at \(s^0\) and then following \(\pi\). COMA [Foerster et al., 2018] implements the multi-agent stochastic policy gradient theorem by replacing the action-value function with the counterfactual advantage function, reducing variance, and not changing the expected gradients.

4 Analysis

In the multi-agent stochastic policy gradient theorem, agent \(a\) learns the policy by directly ascending the approximate marginal joint action value gradient for each \(u_a \in U\), which is scaled by \(M_a (s, u_a, \pi_{-a}) = \sum_{u_{-a}} \pi_{-a} (u_{-a} | \tau_{-a}) Q (s, u)\) (see Equation (2)). Formally, suppose that the optimal and a non-optimal joint action under \(s\) are \(u^*\) and \(u^\#\) respectively, that is, \(Q(s, u^*) > Q(s, u^\#)\). If it holds that \(M_a (s, u^*_a, \pi_{-a}) < M_a (s, u^\#_a, \pi_{-a})\) due to the exploration or suboptimality of other agents’ policies, we possibly have that \(\pi_a (u^*_a | \tau_a) < \pi_a (u^\#_a | \tau_a)\). The centralized policy of agent \(a\) is updated by following policy gradients tailored by the centralized critic, which are negatively affected by other agents’ policies. This issue is called centralized-decentralized mismatch [Wang et al., 2021b]. We will show that centralized-decentralized mismatch occurs in practice for the state-of-the-art MAPG algorithms on the well-known matrix game and differential game in the experimental section.

5 The Proposed Method

In this section, we first propose a novel multi-agent actor-critic method, MAPPG, which learns explicit credit assignment. Then we mathematically prove that MAPPG can address the issue of centralized-decentralized mismatch and the individual policies of MAPPG can converge to the global optimum.

5.1 The Polarization Policy Gradient

In the multi-agent stochastic policy gradient theorem, the scale of the policy gradient of agent \(a\) is impacted by the policies of other agents, which leads to centralized-decentralized mismatch. A straightforward solution is to make the policies of other agents optimal. But here comes a paradox. Learning other agents’ policies depends on the convergence of agent \(a\)’s policy to the global optimum. If agent \(a\)’s policy converges to the global optimum, there seems no need to compute the scale of the policy gradient of agent \(a\). Therefore, we cannot solve the problem of centralized-decentralized mismatch from a policy perspective, we seek to address it from the joint action value perspective.

We define polarization joint action values to replace original joint action values. The polarization joint action values resolve centralized-decentralized mismatch by increasing the distance between the values of the global optimal joint action and the non-optimal joint actions while shortening the distance between the values of multiple non-optimal joint actions. By polarization, the influence of other agents’ non-optimal policies can be largely eliminated. For convenience, the following discussion in the section will assume that the joint action values are fixed in a given state \(s\). In later sections, we will see how the joint action values are updated. If the optimal joint action \(u^*\) in state \(s\) can be identified, then the polarization policy gradient is:

\[
\nabla_\theta J (\pi) = E_\pi \left[ \sum_a \nabla_\theta \log \pi_a (u_a | \tau_a) Q^{PPG} (s, u) \right],
\]

where

\[
Q^{PPG} (s, u) = \begin{cases} 1 & \text{if } u = u^* \\ 0 & \text{otherwise} \end{cases} \tag{3}
\]

is the polarization joint action value function. For each agent, only the gradient of the component of the optimal action is greater than 0, whereby the optimal policy can be learned. However, we cannot traverse all-state-action pairs to find the optimal joint action \(u^*\) in complex scenarios; therefore, a soft version of the polarization joint action value function is defined as:

\[
Q^{PPG} (s, u) = \exp (\alpha Q (s, u)), \tag{4}
\]

where \(\alpha > 0\) denotes the enlargement factor determining the distance between the optimal and the non-optimal joint action values. However, Equation (4) cannot work in practice. On the one hand, the result of the exponential function is easy to overflow. On the other hand, if \(\forall u, Q (s, u) \leq 0\) in state \(s\), the polarization joint action values \(Q^{PPG} (s, u)\) are between 0 and 1. To address the polarization failure, a baseline is introduced as follows:

\[
Q^{PPG} (s, u) = \frac{1}{\beta} \exp (\alpha (Q (s, u) - Q (s, u_{curr}))), \tag{5}
\]

where \(\beta\) is a factor which can prevent exponential gradient explosion and \(u_{curr} = \arg \max_{u_{-a}} \pi_a (u_a | \tau_a)\). By providing a baseline, the policy is guided to pay more attention to the joint actions in \(\{ u : Q (s, u) > Q (s, u_{curr})\}\), which derives a self-improving method. Our method looks similar to COMA [Foerster et al., 2018], but they are different in nature. The baseline in our MAPPG can help solve the centralized-decentralized mismatch. However, the baseline in COMA is introduced to achieve difference rewards.

Adopting polarization joint action values, MAPPG solves the credit assignment issue by applying the following polarization policy gradients:

\[
\nabla_\theta J (\pi) = \frac{1}{\beta} E_\pi \left[ \sum_a \nabla_\theta \log \pi_a (u_a | \tau_a) Q^{PPG} (s, u) \right] = \frac{1}{\beta} \sum_s d^\pi (s) \sum_a \pi_a (u_a | \tau_a) \nabla_\theta \log \pi_a (u_a | \tau_a) \sum_{u_{-a}} \pi_{-a} (u_{-a} | s) Q^{PPG} (s, u_{-a}, u_{-a}). \tag{6}
\]
From Equation (6), we can see that the gradient for action \( u_a \) at state \( s \) is scaled by \( M_{\text{a}}^{\text{PPG}}(s, u_a, \pi_{\text{a}}) = \sum_{u_a'} \pi_{\text{a}}(u_a' \mid s) Q^{\text{PPG}}(s, u_a, u_a') \), which is the polarization marginal joint action value function.

The power function is adopted because it has two properties. (i) The second-order gradient of the power function is greater than 0, so it can increase the distance between the global optimal joint action value and the non-optimal joint action values, while shortening the distance between multiple non-optimal joint action values. (ii) For all \( u \in \{ u : Q(s, u) < Q(s, u_{\text{curr}}) \} \), the corresponding polarization joint action values \( Q^{\text{PPG}}(s, u) \) are between 0 and 1, which makes the policy learning focus more on the domain \( \{ u : Q(s, u) > Q(s, u_{\text{curr}}) \} \) in state \( s \).

### 5.2 Theoretical Proof

In this subsection, we introduce the joint policy improvement for MAPPG and mathematically prove that the individual policies of MAPPG can converge to the global optimum. For convenience, this section will be discussed in a fully observable environment, where each agent chooses actions based on the state instead of the action-observation history. To ensure the uniqueness of the optimal joint action, we make the following assumption.

**Assumption 1.** The joint action value function \( Q(s, u) \) has one unique maximizing joint action for all \( s \in S \) and \( |U| < \infty \).

First, we mathematically prove that each maximizing individual action of the polarization marginal joint action value function is consistent with the maximizing joint action’s corresponding component of the joint action value function in Theorem 1.

**Theorem 1** (Optimality Consistency). Let \( \pi \) be a joint policy. Let \( u^* = \arg \max_{u \in U} Q(s, u) \) and \( u^{\text{sec}} = \arg \max_{u \in \{ U \cup \{ u^* \} \}} Q(s, u) \). If it holds that \( \forall a \in A, \alpha > \frac{\log \pi_{\text{a}}(u^*_a \mid s) - Q(s, u^{\text{sec}}) - Q(s, u^*)}{Q(s, u^{\text{sec}}) - Q(s, u^*)} \), then we have that for all individual actions \( u'_a \),

\[
M_{\text{a}}^{\text{PPG}}(s, u'_a, \pi_{\text{a}}) < M_{\text{a}}^{\text{PPG}}(s, u^*_a, \pi_{\text{a}}),
\]

where \( u'_a \neq u^*_a \).

**Proof.** See Appendix A.

Theorem 1 reveals an important insight. The enlargement factor regulates the distance between the optimal and non-optimal action values, and MAPPG tackles the challenge of centralized-decentralized mismatch with \( \alpha > \frac{\log \pi_{\text{a}}(u^*_a \mid s) - Q(s, u^*)}{Q(s, u^{\text{sec}}) - Q(s, u^*)} \).

Second, first-order optimization algorithms for training deep neural networks are difficult to ensure global convergence [Goodfellow et al., 2016]. Hence, one assumption on policy parameterizations is required for our analysis.

**Assumption 2.** Given the function \( \psi : S \times U \to \mathbb{R} \), agent \( a \)'s policy \( \pi_{\text{a}}(\cdot \mid s) \) is the corresponding vector of action probabilities given by the softmax parameterization for all \( u'_a \in U \), i.e.,

\[
\pi_a(u_a | s) = \frac{\exp (\psi_{s,u_a})}{\sum_{u'_a \in U} \exp (\psi_{s,u'_a})},
\]

where \( \psi_{s,u_a} \equiv \psi(s, u_a) \) with \( |U| < \infty \).

Then, following the standard optimization result of Theorem 10 [Agarwal et al., 2021], we prove that the single agent policy converges to the global optimum for the softmax parameterization in Lemma 1.

**Lemma 1** (Individual Policy Improvement). Let the joint action values remain unchanged during the policy improvement. Let \( \pi^0 = [\pi^0_a]_{a=1} \) be the initial joint policy and \( \psi_{s,a} \) be the the corresponding vector of \( \psi_{s,a} \), for all \( u_a \in U \). The update for agent \( a \) in state \( s \) at iteration \( t \) with the stepsize \( \eta \leq \frac{(1-\alpha)^2}{8} \) is defined as follows:

\[
\psi^t_{s,a} = \psi^t_{s,a} + \eta \nabla_{\psi_{s,a}} V_{s,a} (\pi^t_{s,a}, \pi_{-a}^0),
\]

where

\[
V_{s,a}^t (\pi^t_{s,a}, \pi_{-a}^0) = \sum_{u_a} \pi^t_{a} (u_a \mid s) M_{\text{a}}^{\text{PPG}}(s, u_a, \pi_{-a}^0).
\]

Then, we have that \( \pi^t_a \to \pi^*_a \) as \( t \to \infty \), where \( \arg \max_{u_a} \pi^*_a (u_a | s) = \arg \max_{u_a} M_{\text{a}}^{\text{PPG}}(s, u_a, \pi_{-a}^0) \).

**Proof.** See Appendix B.

Finally, we prove that optimal individual policies can be attained as long as MAPPG applies individual policy improvement to all agents in Theorem 2.

**Theorem 2** (Joint Policy Improvement). Let the joint action values remain unchanged during the policy improvement. Let \( u^* = \arg \max_{u \in U} Q(s, u) \) and \( u^{\text{sec}} = \arg \max_{u \in \{ U \cup \{ u^* \} \}} Q(s, u) \). Let the joint policy at iteration \( t \) be \( \pi^t = [\pi^t_a]_{a=1} \). If individual policy improvement is applied to each agent \( a \in A \) and \( \alpha > \frac{\log \pi^t_{a} (u^*_a \mid s) - Q(s, u^{\text{sec}}) - Q(s, u^*)}{Q(s, u^{\text{sec}}) - Q(s, u^*)} \), then we have that \( \pi^t \to \pi^* \) as \( t \to \infty \), where \( \arg \max_{u_a} \pi^* (u_a | s) = \arg \max_{u_a} Q(s, u) \).

**Proof.** See Appendix B.

Although Theorem 2 requires that when optimizing the policy of a single agent, other agents’ policies should be maintained as \( \pi^0_{-a} \), MAPPG replaces \( \pi^0_{-a} \) with the current policies \( \pi^t_{-a} \) of other agents in practice, which is a more efficient sampling strategy. This change does not compromise optimality empirically.

### 5.3 MAPPG Architecture

The overall framework of MAPPG is illustrated in Figure 1. For each agent \( a \), there is an individual actor \( \pi_{\text{a}}(u_a | \tau_a) \) parameterized by \( \theta_a \). We denote the joint policy as \( \pi = [\pi^*_a]_{a=1} \). Two centralized components are critics \( Q(s, u) \) and target critics \( Q_{\text{target}}(s, u) \), parameterized by \( \phi \) and \( \phi^* \).

At the execution phase, each agent selects actions w.r.t. the current policy and exploration based on local observations in a decentralized manner. By interacting with the environment,
the transition tuple \( e = (s, [z_a]_{a=1}^n, u, r, s', [z'_a]_{a=1}^n) \) is added to the buffer \( D \).

At the training phase, mini-batches of experiences are sampled from the buffer uniformly at random. We train the parameters of critics to minimize the 1-step TD loss by descending their gradients according to:

\[
\nabla_{\phi} L_{td} (\phi) = \nabla_{\phi} \mathbb{E}_{e \sim D} \left[ (y - Q(s, u))^2 \right],
\]

(7)

where \( y = r + \gamma \max_{a'} \pi (u' | r') \). In the proof of Theorem 2, some strong constraints need to be satisfied. To derive a practical algorithm, we must make approximations. First, MAPPG adopts target critics for individual policy improvement as an implementation of fixed joint action values. Second, the estimation of the Q-value has aleatoric uncertainty and epistemic uncertainty. Without a constraint, maximization of \( J(\pi) \) with polarization would lead to an excessively large policy update; hence, we now consider how to modify the objective. We apply the pessimistic bound of \( Q^{PPG} \) with the help of two target critics \( \{Q_1^{target}, Q_2^{target}\} \) and penalize changes to the policy that make \( Q^{PPG} \) larger than \( L \). We train two critics, which are learned with the same training setting except for the initialization parameters. The two target critics share the same network structure as that of the two critics, and the parameters of the two target critics are periodically synchronized with those of the two critics, respectively. We train the parameters of actors to maximize the expected polarization Q-function which is called the MAPPG loss by ascending their gradients according to:

\[
\nabla_{\theta} J(\pi) = \frac{1}{\beta} \mathbb{E}_{\pi} \left[ \sum_a \nabla_{\theta_a} \log \pi_a (u_a | \tau_a) \min \left( \hat{Q}^{PPG} (s, u), L \right) \right],
\]

(8)

where

\[
\hat{Q}^{PPG} (s, u) = \exp \left( \alpha \left( \min_{k \in \{1, 2\}} Q_k^{target} (s, u) - \max_{k \in \{1, 2\}} Q_k^{target} (s, u_{curr}) \right) \right).
\]

To prevent vanishing gradients caused by the increasing action probability with an inappropriate learning rate in practice, the gradients for the joint action \( u \) are set to 0 if \( \hat{Q}^{PPG} (s, u) < 1 \) or \( \forall a, \pi_a (u_a | \tau_a) > P \) where \( P \geq 0.5 \), which is called the policy gradient clipping. For completeness, we summarize the training of MAPPG in the Algorithm 1. More details are included in Appendix C.

6 Experiments

In this section, first, we empirically study the optimality of MAPPG for discrete and continuous action spaces. Then, in StarCraft II, we demonstrate that MAPPG outperforms state-of-the-art MAPG algorithms. By ablation studies, we verify the effectiveness of our polarization joint action values and the pessimistic bound of \( Q^{PPG} \). We further perform an ablation study to verify the effect of different enlargement factors on convergence to the optimum. In matrix and differential games, the worst result in the five training runs with different random seeds is selected to exclude the influence of random initialization parameters of the neural network. All the learning curves are plotted based on five training runs with different random seeds using mean and standard deviation in StarCraft II and the ablation experiment.

6.1 Matrix Game and Differential Game

In the discrete matrix and continuous differential games, we investigate whether MAPPG can converge to the global optimum compared with existing MAPG algorithms, including MADDPG [Lowe et al., 2017], COMA [Foerster et al.,
Algorithm 1 MAPPG

1: for episode = 1 to max\_training\_episode do
2: Initialize the environment
3: for $t = 1$ to max\_episode\_length do
4: For all agents, get the current state $s$ and observations $\{z_a\}_{a=1}^A$, choose a joint action $u$ w.r.t. the current policy and exploration
5: Execute the joint action $u$, observe a reward $r$, and get the next state $s'$ and observations $\{z'_a\}_{a=1}^A$
6: Add the transition $(s, \{z_a\}_{a=1}^A, u, r, s', \{z'_a\}_{a=1}^A)$ to the buffer $D$
7: if time\_to\_update\_actors\_and\_critics then
8: Sample a random minibatch of $K$ samples from $D$
9: Update $\phi$ by descending their gradients according to Equation (7)
10: Update $\theta$ by ascending their gradients according to Equation (8) with the policy gradient clipping
11: end if
12: if time\_to\_update\_target\_critics then
13: Replace target parameters $\phi^\_i \leftarrow \phi_i$ for $i \in \{1, 2\}$
14: end if
15: end for
16: end for

2018], DOP [Wang et al., 2021b], FACMAC [Peng et al., 2021], and FOP [Zhang et al., 2021]. The two games have one common characteristic: some destructive penalties are around with the optimal solution [Zhang et al., 2021], which triggers the issue of the centralized-decentralized mismatch.

| $u_2$ | $u_1$ | $A$ | $B$ | $C$ |
|-------|-------|-----|-----|-----|
| $A$   | 15    | -12 | -12 |     |
| $B$   | -12   | 10  | 10  |     |
| $C$   | -12   | 10  | 10  |     |

(a) Payoff of matrix game

| $\pi_2$ | $\pi_1$ | $A$ | $B$ | $C$ |
|---------|---------|-----|-----|-----|
| $\pi_1$ | 0.0(A)  | 0.7(B) | 0.3(C) |
| $0.0(A)$ | -32.5 | -11.2 | -11.2 |
| $0.9(B)$ | -11.4 | 9.9  | 9.9  |
| $0.1(C)$ | -11.5 | 9.9  | 9.9  |

(b) COMA: $\pi_1, \pi_2, Q$

| $\pi_2$ | $\pi_1$ | $A$ | $B$ | $C$ |
|---------|---------|-----|-----|-----|
| $\pi_1$ | 0.0(A)  | 0.5(B) | 0.5(C) |
| $0.0(A)$ | -11.5 | -11.5 | -11.5 |
| $0.5(B)$ | -11.5 | 9.9  | 9.9  |
| $0.5(C)$ | -11.5 | 9.9  | 9.9  |

(c) DOP: $\pi_1, \pi_2, Q$

| $\pi_2$ | $\pi_1$ | $A$ | $B$ | $C$ |
|---------|---------|-----|-----|-----|
| $\pi_1$ | 0.0(A)  | 0.3(B) | 0.3(C) |
| $0.0(A)$ | -9.1  | -4.4  | -7.4  |
| $0.0(B)$ | -5.3  | 9.0   | 5.0   |
| $0.0(C)$ | -2.6  | 9.0   | 9.7   |

(d) FACMAC: $\pi_1, \pi_2, Q$

| $\pi_2$ | $\pi_1$ | $A$ | $B$ | $C$ |
|---------|---------|-----|-----|-----|
| $\pi_1$ | 0.4(A)  | 0.3(B) | 0.3(C) |
| $0.4(A)$ | 15.2  | -12.2 | -12.2 |
| $0.3(B)$ | -12.0 | 10.0  | 10.0  |
| $0.3(C)$ | -12.0 | 10.0  | 10.0  |

(e) FOP: $\pi_1, \pi_2, Q$

| $\pi_2$ | $\pi_1$ | $A$ | $B$ | $C$ |
|---------|---------|-----|-----|-----|
| $\pi_1$ | 0.4(A)  | 0.3(B) | 0.3(C) |
| $0.4(A)$ | 15.2  | -12.2 | -12.2 |
| $0.3(B)$ | -12.0 | 10.0  | 10.0  |
| $0.3(C)$ | -12.0 | 10.0  | 10.0  |

(f) MAPPG: $\pi_1, \pi_2, Q$

Table 1: The cooperative matrix game. Boldface means the optimal greedy actions from individual policies.

Matrix Game

The matrix game is shown in Table 1 (a), which is the modified matrix game proposed by QTRAN [Son et al., 2019]. This matrix game captures a cooperative multi-agent task where we have two agents with three actions each. We show the results of COMA, DOP, FACMAC, FOP, and MAPPG over 10k steps, as in Table 1 (b) to (f) respectively. MAPPG uses an $\epsilon$-greedy policy in which $\epsilon$ is annealed from 1 to 0.05 over 10k steps. Note that MAPPG is the only algorithm that can successfully converge to the optimum. The results of these algorithms on the original matrix game proposed by QTRAN [Son et al., 2019], and more details are included in Appendix C.

Figure 2: Learning paths of different algorithms in the MTQ game. The horizontal and vertical axes represent $u_1$ and $u_2$, respectively. All the points on a given contour line are all at the same joint action values. The shallow red and dark red indicate the start and end of the learning paths, respectively.

**Differential Game**

The differential game is the modification of the Max of Two Quadratic (MTQ) Game from previous literature [Zhang et al., 2021]. This is a single-state continuous game for two agents, and each agent has a one-dimensional bounded continuous action space $([-10, 10])$ with a shared reward function. In Equation (9), $u_1$ and $u_2$ are the actions of two agents and $r(u_1, u_2)$ is the shared reward function received by two agents. There is a sub-optimal solution $0$ at $(-5, -5)$ and a global optimal solution $5$ at $(5, 5)$.

\[
\begin{align*}
&f_1 = 0.8 \times \left[-\left(\frac{u_1+5}{5}\right)^2 - \left(\frac{u_2+5}{5}\right)^2\right] \\
&f_2 = 1 \times \left[-\left(\frac{u_1-5}{5}\right)^2 - \left(\frac{u_2-5}{5}\right)^2\right] + 5 \\
&r(u_1, u_2) = \max(f_1, f_2)
\end{align*}
\]
Gaussian noise. We use Gaussian noise with mean 0 and standard deviation 1. The learning paths (20k steps) of all algorithms are shown as red dots in Figure 2 (a) to 2 (d). MAPPG consistently converges to the global optimum while all other algorithms fall into the sub-optimum. MADDPG can estimate \( r(u_1, u_2) \) accurately, but fail to converge to the global optimum. However, the regular decomposed actor-critic algorithms (FACMAC and FOP) converge to the sub-optimum and also have limitations to express \( r(u_1, u_2) \). The results of these algorithms for the original MTQ game used by previous literature [Zhang et al., 2021], and more details are included in Appendix C.

6.2 StarCraft II

We evaluate MAPPG on the challenging StarCraft Multi-Agent Challenge (SMAC) benchmark [Samvelyan et al., 2019] in eight maps, including 3s_vs_4z, 3s_vs_5z, 5m_vs_6m, 8m_vs_9m, 10m_vs_11m, 27m_vs_30m, MMM2 and 3s5z_vs_3s6z. The other algorithms include 5 state-of-the-art MAPG algorithms (COMA, MADDPG, stochastic DOP, FOP, FACMAC). MAPPG uses an \( \epsilon \)-greedy policy in which \( \epsilon \) is annealed from 1 to 0.05 over 50k steps. Results are shown in Figure 3 and MAPPG outperforms other algorithms in the final performance. More details of the StarCraft II experiments are included in Appendix C.

6.3 Ablation Studies

In Figure 4 (a), the comparison between the MAPPG and MAPPG without the pessimistic bound demonstrates the importance of making conservative policy improvements, which can alleviate the problem of excessively large policy updates caused by inaccurate value function estimation. The comparison between the MAPPG and MAPPG without the polarization demonstrates the contribution of polarization joint action values to global convergence. In Figure 4 (b), we observe that MAPPG can converge to a policy that can obtain a reward closer to the optimal reward as the increase of the enlargement factor. The discrepancy between the learning curve of \( \alpha = \{1, 2\} \) and other learning curves indicates the influence of polarization. The difference in performance of different \( \alpha \) is consistent with Theorem 1 and 2 even in the continuous action space.

7 Conclusion

This paper presents MAPPG, a novel multi-agent actor-critic framework that allows centralized end-to-end training and efficiently learns to do credit assignment properly to enable decentralized execution. MAPPG takes advantage of the polarization joint action value that efficiently guarantees the consistency between individual optimal actions and the joint optimal action. Theoretical analysis shows that MAPPG can converge to optimality. Empirically, MAPPG achieves competitive results compared with state-of-the-art MAPG algorithms for large-scale complex multi-agent cooperations.

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