Mixed Reinforcement Learning with Additive Stochastic Uncertainty

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Abstract—Reinforcement learning (RL) methods often rely on massive exploration data to search optimal policies, and suffer from poor sampling efficiency. This paper presents a mixed reinforcement learning (mixed RL) algorithm by simultaneously using dual representations of environmental dynamics to search the optimal policy with the purpose of improving both learning accuracy and training speed. The dual representations indicate the environmental model and the state-action data: the former can accelerate the learning process of RL, while its inherent model uncertainty generally leads to worse policy accuracy than the latter, which comes from direct measurements of states and actions. In the framework design of the mixed RL, the compensation of the additive stochastic model uncertainty is embedded inside the policy iteration RL framework by using explored state-action data via iterative Bayesian estimator (IBE). The optimal policy is then computed in an iterative way by alternating between policy evaluation (PEV) and policy improvement (PIM). The convergence of the mixed RL is proved using the Bellman’s principle of optimality, and the recursive stability of the generated policy is proved via the Lyapunov’s direct method. The effectiveness of the mixed RL is demonstrated by a typical optimal control problem of stochastic non-affine nonlinear systems (i.e., double lane change task with an automated vehicle).

Index Terms—Reinforcement learning, Bayesian estimation, Policy evaluation (PEV), Policy improvement (PIM), Dynamic model

I. INTRODUCTION

REINFORCEMENT learning (RL) has been successfully applied in a variety of challenging tasks, such as Go game and robotic control [1], [2]. The increasing interest in RL is primarily stimulated by its data-driven nature, which requires little prior knowledge of the environmental dynamics, and its combination with powerful function approximators, e.g. deep neural networks. In spite of these advantages, many purely data-driven RL suffers from slow convergence rate in continuous action space of stochastic systems, which hinders its widespread adoption in real-world applications [3], [4].

To alleviate this problem, researchers have investigated the use of model-driven RL algorithms, which searches the optimal policy with known environmental models by employing the principle of Bellman optimality [5]–[8]. Model-driven RL has shown faster convergence compared to the data-driven counterparts, since environmental models provide the information of environmental evolution in the whole state-action space. Thus, gradient calculation can be easier and more accurate than merely using data samples [9]. To solve the Bellman equation in the continuous action space, most existing RL methods adopt an iterative technique to gradually find the optimum. One classic framework is called policy iteration RL, which consists of two steps: 1) policy evaluation (PEV), that aims at solving self-consistency condition equation and evaluating the current policy, and 2) policy improvement (PIM) that seeks to optimize the corresponding value function [10], [11].

A number of prior works focus on improving the PEV step by using model-driven value expansion, which corrects the cumulative return or the approximated value function by using environmental models [12], [13]. However, due to the inherent model inaccuracy, this technique is not suitable for long-term PEV. To partly solve this problem, model-based value expansion algorithm proposed a hybrid algorithm that uses environmental dynamic model only to simulate the short-term horizon, and utilizes the explored data to estimate the long-term value beyond the simulation horizon [14]. Nevertheless, the inaccuracy problem hinders the application of environmental model in PEV.

So far, the environmental model has limited applications in the PIM step due to two main issues: 1) the inaccuracy and overfitting of environmental dynamic models and 2) policy oscillation caused by the time-varying models, since the system model is iteratively learned or updated in the training process [15]–[17]. Prior works provide the model ensemble technique for solving these problems. For example, the model-ensemble trust region policy optimization (TRPO) algorithm [18] limits model over-training by using an ensemble metric during policy search. The stochastic ensemble value expansion [19], which is an extension to the model-based value expansion, interpolates between many different horizon lengths and different models to favor models that generate more accurate estimates. Although the ensemble techniques effectively avoid over-fitting, it brings extra computational overhead.

Facing the aforementioned challenges of RL algorithms, this paper proposes a mixed reinforcement learning (mixed RL) algorithm that utilizes the dual representations of environmental dynamics to improve both learning accuracy and training speed. The environmental model, either empirical or theoreti-
cal, is used as the prior information to avoid overfitting, while the model error is iteratively compensated by the measured data of states and actions using Bayesian estimation. Precisely, the contributions of this paper are as follows,

1. A dual representation of environmental dynamics is utilized in RL by integrating the designer’s knowledge with the measured data. An iterative Bayesian estimator (IBE) with explored data is designed for improving the model accuracy and computation efficiency.

2. A mixed RL algorithm is developed by embedding the iterative Bayesian estimator into the policy iteration. We propose the sufficient recursive stability and convergence condition which limits the estimated difference of iterative Bayesian estimator between two consecutive iterations. And we proved that the sufficient condition holds with probability one after sufficient iterations.

The rest of this paper is organized as follows. Section II defines a mixed RL problem. Section III introduces the mixed representation of environmental dynamics. Section IV and Section V presents the mixed RL algorithm, as well as the parametrization of the policy and value function. Section VI evaluates the effectiveness of mixed RL problem using the double lane change task with an automated vehicle, and Section VII concludes this paper.

II. PROBLEM DESCRIPTION

We consider a discrete-time environment with additive stochastic uncertainty and its actual dynamics is mathematically described as

\[
x_{t+1} = f(x_t, u_t) + \xi_t, \quad \xi_t \sim N(\mu, K)
\]

where \( t \) is the current time, \( x_t \in \mathcal{X} \subset \mathbb{R}^n \) is the state, \( u_t \in \mathcal{U} \subset \mathbb{R}^m \) is the action, \( f(\cdot, \cdot) \) is the deterministic part of environmental dynamics, \( \xi_t \in \mathbb{R}^n \) is the additive stochastic uncertainty with unknown mean \( \mu \in \mathbb{R}^n \) and covariance \( K \in \mathbb{R}^{n \times n} \). In this study, we assume that the additive stochastic uncertainty \( \xi_t \) follows the Gaussian distribution and \( \mathbb{E}\{|\xi_t|\} < \infty \). Parameters \( \mu \) and \( K \) can be completely independent of \( (x, u) \) or form a functional relationship with \( (x, u) \).

As shown in Fig. 1, actual environmental dynamics contains both deterministic part \( f(\cdot, \cdot) \) and uncertain part \( \xi_t \), where \( p(\xi_t) \) is the probability density of \( \xi_t \) and \( p(x_{t+1}) \) is the probability density of \( x_{t+1} \) under given \((x_t, u_t)\).

The objective of mixed RL is to minimize the expectation of cumulative cost under the distribution of additive stochastic uncertainty \( \xi_t \), shown as (2):

\[
\min_{\pi} \mathbb{E}_\xi \left\{ \sum_{k=0}^{\infty} \gamma^k l(x_{t+k+1}, u_{t+k}) \right\}, \quad \forall x_t \in \mathcal{X}
\]

where \( \pi \) is policy, \( V(\cdot) \) is the state value, which is a function of initial state \( x_t \), \( l(\cdot, \cdot) \geq 0 \) is the utility function, which is positive definite, \( \gamma \) is the discounting factor with \( 0 < \gamma < 1 \), and \( \mathbb{E}_\xi(\cdot) \) is the expectation w.r.t. the additive stochastic uncertainty \( \xi_t \). Here, the policy is a deterministic mapping:

\[
u_t = \pi(x_t)
\]

The optimal cost function is defined as

\[
V^*(x_t) = \min_{u_t} \mathbb{E}_\xi \{l(x_{t+1}, u_t) + \gamma V^*(x_{t+1})\}
\]

where \( \{u_t, u_{t+1}, \ldots, u_\infty\} \) is the action sequence starting from time \( t \). In mixed RL, the self-consistency condition (5) is used to describe the relationship of state values between current time and next time:

\[
V(x_t) = \mathbb{E}_\xi \{l(x_{t+1}, u_t) + \gamma V(x_{t+1})\}
\]

By using Bellman’s principle of optimality, we have the well-known Bellman equation:

\[
V^*(x_t) = \min_{u_t} \mathbb{E}_\xi \{l(x_{t+1}, u_t) + \gamma V^*(x_{t+1})\}
\]

The Bellman equation implies that optimal policy can be calculated in a step-by-step backward manner. Therefore, optimal action is

\[
\pi^*(x_t) \triangleq \arg \min_{u_t} \mathbb{E}_\xi \{l(x_{t+1}, u_t) + \gamma V^*(x_{t+1})\}
\]

where \( \pi^*(\cdot) \) represent the optimal policy that maps from an arbitrary state \( x \) to its optimal action \( u^* \). Similar to other indirect RL problems, mixed RL aims to find an optimal policy by minimizing cost (2) while being subjected to the constraints of environmental dynamics. The searching procedure can be replaced by solving the Bellman equation in an iterative way.

Obviously, the performance of the generated policy depends on the accuracy of the representation of the environmental dynamics. In fact, even an analytical model or state-action samples \( \{x_1, u_1, \ldots, x_k, u_k, \ldots\} \) can be an useful representation, which corresponds to the so-called model-driven RL and data-driven RL, respectively. The analytical model is usually inaccurate due to environmental uncertainties, which will impair the optimality of the generated policy. The state-action samples, on the other hand, have low sampling efficiency and will slow down the training process.
III. DUAL REPRESENTATION OF ENVIRONMENTAL DYNAMICS

In mixed RL, the environmental dynamics are dually represented by both an analytical model $M$ and state-action data $D$. The former represents the designer’s knowledge about the environmental dynamics. It is defined in the whole state-action space and can be used to accelerate the training speed. The latter comes from direct measurement of state-action pairs during learning. It is generally more accurate than $M$, and therefore can improve the estimation of the uncertain part in the analytical model. The mixed RL uses the dual representation of environmental dynamics, i.e., both analytical model $M$ and state-action data $D$, to search for optimal policy. Such dual representation can have accelerated training compared to purely data-driven RL while achieving better policy satisfaction than purely model-driven counterpart.

The analytical model $M$ is similar to (1):

$$\mathcal{M} = \{x_{t+1} = f(x_t, u_t) + \xi_t^M\}$$

where the mean $\mu_M$ and covariance $K_M$ of $\xi_t^M$ are given in advance by designers. The given distribution can be quite different from actual distribution due to the modeling errors. Here, $\mu_M$ and $K_M$ are taken as the prior knowledge of environmental dynamics.

The state-action data, i.e., a sequence of triples $(x_j, u_j, x_{j+1})$, is denoted by $D$:

$$D = \{(x_j^D, u_j^D, x_{j+1}^D), j = 1, 2, \ldots, N\}$$

where $x_j^D$ is the $j$-th state in $D$, $u_j^D$ is the $j$-th action in $D$, and $N$ is the length of data samples. Obviously, the measured data also inherently contain the distribution information of $\xi$, and are taken as the posterior knowledge of environmental dynamics.

If the environmental dynamics is exactly known, optimal policy $\pi^*(\cdot)$ can be computed by only using the dynamic model, which is also the most efficient RL. However, exact model is inaccessible in reality, and thus the generated policy might not converge to $\pi^*(\cdot)$. Although collecting samples $D$ is less efficient, it can be quite accurate to represent the environment, thus being able to improve the generated policy. Therefore, the mixed representation is able to utilize advantages of both model $M$ and data $D$ to improve training efficiency and policy accuracy.

**Improve model $M$ by using data $D$:**

We utilize data samples to improve the estimation of the additive stochastic uncertainty $\xi$ in the analytical model $M$. The uncertainty that inherently exists in a state-action triple is equal to

$$\xi_j^D = x_{j+1}^D - f(x_j^D, u_j^D)$$

A Bayesian estimator is adopted to fuse the distribution information of the additive stochastic uncertainty from both model $M$ and data $D$. The Bayesian estimator aims to maximize the posterior probability $p(\mu, K|D)$. In general, we introduce $p(\mu)$ and $p(K)$ as the the prior distribution of $\mu$ and $K$, then the maximum likelihood problem becomes

$$\max_{\mu, K} \left\{ p(\mu, K|D) \right\}$$

$$\Leftrightarrow \max_{\mu, K} \left\{ p(D|\mu, K) p(\mu)p(K) \right\}$$

Under the assumption that data $D$ is iid, (11) can be rewritten into iterative form:

$$\max_{\mu, K} \left\{ p(D|\mu, K) p(\mu)p(K) \right\}$$

$$D_{k-1} = \{\xi_1^D, \xi_2^D, \ldots, \xi_{k-1}^D\}$$

Therefore, we can build an iterative Bayesian estimator IBE(·) with the following general form,

$$\left[ \begin{array}{c} \mu_k \\ K_k \end{array} \right] = \text{IBE} \left( \mu_{k-1}, K_{k-1}, \xi_k^D \right)$$

Here, we discuss two simplified cases of the Bayesian estimator:

**Case 1:** Assume that the covariance $K$ is known and $\mu$ is independent from $x$ and $u$, we introduce $\mu \sim \mathcal{N}(\mu_M, K_M)$ provided by model $M$ as the prior distribution of $\mu$. Thus, the objective function $L$ of Bayesian estimation becomes,

$$\mathcal{L} = -\log \left\{ p(D|\mu)p(\mu) \right\}$$

$$= \frac{1}{2} (\mu - \mu_M)^T K_M^{-1} (\mu - \mu_M)$$

$$+ \frac{1}{2} \sum_{j=1}^N (\xi_j^D - \mu)^T K^{-1} (\xi_j^D - \mu) + \mathcal{C}$$

where $p(\mu) = \mathcal{N}(\mu_M, K_M)$ is the prior distribution and $\mathcal{C}$ is a constant. The optimal estimation of $\mu$ is calculated by (15).

$$\mu_k = (K_M^{-1} + NK^{-1})^{-1} \left( K_M^{-1} \mu_M + K^{-1} \sum_{j=1}^N \xi_j^D \right)$$

The $\mu_k$ can be iteratively computed by using IBE. Define $\Psi_k = K_M^{-1} + kk^{-1}$, and $m_k = \sum_{j=1}^k \xi_j^D$, the iterative Bayesian estimator IBE(·) is

$$\Psi_k = \Psi_{k-1} + K^{-1}$$

$$m_k = m_{k-1} + \xi_k^D$$

$$\mu_k = (\Psi_k)^{-1} \left( K_M^{-1} \mu_M + K^{-1} m_k \right)$$

**Case 2:** Assume that both the mean $\mu$ and covariance $K$ are unknown. The same prior distribution in case 1 is applied to $\mu$. The covariance $K$ is estimated by the maximum likelihood estimation, since the parameters of the prior distribution of $K$ are inconvenient to determine by human designer. Subsequently, the optimal estimation of $\mu$ and $K$ are as follows,

$$\hat{\mu} = (K_M^{-1} + NK^{-1})^{-1} \left( K_M^{-1} \mu_M + K^{-1} \sum_{j=1}^N \xi_j^D \right)$$

$$\hat{K} = \frac{1}{N} \sum_{j=1}^N (\xi_j^D - \hat{\mu}) (\xi_j^D - \hat{\mu})^T$$

$$\Rightarrow \max_{\mu, K} \left\{ p(\mu, K|D) \right\}$$

$$\Leftrightarrow \max_{\mu, K} \left\{ p(D|\mu, K) p(\mu)p(K) \right\}$$

Under the assumption that data $D$ is iid, (11) can be rewritten into iterative form:

$$\max_{\mu, K} \left\{ p(D|\mu, K) p(\mu)p(K) \right\}$$

$$D_{k-1} = \{\xi_1^D, \xi_2^D, \ldots, \xi_{k-1}^D\}$$

Therefore, we can build an iterative Bayesian estimator IBE(·) with the following general form,

$$\left[ \begin{array}{c} \mu_k \\ K_k \end{array} \right] = \text{IBE} \left( \mu_{k-1}, K_{k-1}, \xi_k^D \right)$$

Here, we discuss two simplified cases of the Bayesian estimator:

**Case 1:** Assume that the covariance $K$ is known and $\mu$ is independent from $x$ and $u$, we introduce $\mu \sim \mathcal{N}(\mu_M, K_M)$ provided by model $M$ as the prior distribution of $\mu$. Thus, the objective function $L$ of Bayesian estimation becomes,

$$\mathcal{L} = -\log \left\{ p(D|\mu)p(\mu) \right\}$$

$$= \frac{1}{2} (\mu - \mu_M)^T K_M^{-1} (\mu - \mu_M)$$

$$+ \frac{1}{2} \sum_{j=1}^N (\xi_j^D - \mu)^T K^{-1} (\xi_j^D - \mu) + \mathcal{C}$$

where $p(\mu) = \mathcal{N}(\mu_M, K_M)$ is the prior distribution and $\mathcal{C}$ is a constant. The optimal estimation of $\mu$ is calculated by (15).

$$\mu_k = (K_M^{-1} + NK^{-1})^{-1} \left( K_M^{-1} \mu_M + K^{-1} \sum_{j=1}^N \xi_j^D \right)$$

The $\mu_k$ can be iteratively computed by using IBE. Define $\Psi_k = K_M^{-1} + kk^{-1}$, and $m_k = \sum_{j=1}^k \xi_j^D$, the iterative Bayesian estimator IBE(·) is

$$\Psi_k = \Psi_{k-1} + K^{-1}$$

$$m_k = m_{k-1} + \xi_k^D$$

$$\mu_k = (\Psi_k)^{-1} \left( K_M^{-1} \mu_M + K^{-1} m_k \right)$$

**Case 2:** Assume that both the mean $\mu$ and covariance $K$ are unknown. The same prior distribution in case 1 is applied to $\mu$. The covariance $K$ is estimated by the maximum likelihood estimation, since the parameters of the prior distribution of $K$ are inconvenient to determine by human designer. Subsequently, the optimal estimation of $\mu$ and $K$ are as follows,

$$\hat{\mu} = (K_M^{-1} + NK^{-1})^{-1} \left( K_M^{-1} \mu_M + K^{-1} \sum_{j=1}^N \xi_j^D \right)$$

$$\hat{K} = \frac{1}{N} \sum_{j=1}^N (\xi_j^D - \hat{\mu}) (\xi_j^D - \hat{\mu})^T$$

$$\Rightarrow \max_{\mu, K} \left\{ p(\mu, K|D) \right\}$$

$$\Leftrightarrow \max_{\mu, K} \left\{ p(D|\mu, K) p(\mu)p(K) \right\}$$

Under the assumption that data $D$ is iid, (11) can be rewritten into iterative form:
Define $\Psi_k = K_{M}^{-1} + k\hat{K}_k^{-1}$ and $m_k = \sum_{j=1}^{k} \xi_j^D$. Then $\hat{\mu}$ and $\hat{K}$ can be iteratively computed by the following IBE,

$$\Psi_k = \Psi_{k-1} + \hat{K}_{k-1}^{-1}$$
$$m_k = m_{k-1} + \xi_k^D$$
$$\hat{\mu}_k = (\Psi_k)^{-1} \left( K_{M}^{-1} \mu_M + \hat{K}_{k-1}^{-1} m_k \right)$$
$$\hat{K}_k = \frac{1}{k} \left\{ (k-1)\hat{K}_{k-1} + (\xi_k^D - \hat{\mu}_{k-1}) (\xi_k^D - \hat{\mu}_{k-1})^T \right\}$$

For more general cases where $\mu$ is related to $x$ and $u$, i.e., $\mu = \phi(x,u,w_{\phi})$, where $\phi(\cdot)$ is a general function with parameter $w_{\phi}$, the likelihood $L$ becomes (19) and the optimal estimation of $w_{\phi}$ is the minimum of $L$.

$$p(\mu) \propto p(w_{\phi})$$
$$L = \log \left\{ p(D|\mu = \phi(x,u,w_{\phi}))p(w_{\phi}) \right\}$$

IV. MIXED RL ALGORITHM

A. Mixed RL Algorithm Framework

Existing RL algorithms that compute the optimal policy via the use of Bellman equation are known as indirect RL and they usually involve PEV and PIM steps. Different from traditional indirect RL algorithms, mixed RL consists of three alternating steps, i.e., IBE, PEV and PIM, as shown in Fig. 2. IBE that is proposed in Section III is used to estimate the mean and covariance of the additive stochastic uncertainty iteratively. PEV seeks to numerically solve a group of algebraic equations governed by the self-consistency condition (5) under current-step policy $\pi$, and PIM is to search a better policy by minimizing a “weak” Bellman equation.

![Fig. 2. The framework of the mixed RL algorithm.](image)

In the first step, IBE calculates $\hat{\mu}_k$ and $\hat{K}_k$ with the latest data $\xi_k^D$ and the mixed model is updated accordingly, i.e.,

$$x' = f(x,u) + \xi_k, \quad \hat{\xi}_k \sim N(\hat{\mu}_k, \hat{K}_k)$$

(20)

where $[\hat{\mu}_k, \hat{K}_k] = \text{IBE}(\mu_{k-1}, K_{k-1}, \xi_k^D)$ is defined in (13). The optimal policy is searched by policy iteration with the mixed model (20). In the second step, PEV solves (21) under the estimated distribution of $\xi$:

$$V^k(x) = \mathbb{E}_{\hat{\xi}_k} \left\{ l(x', \pi^k(x)) + \gamma V^k(x') \right\}, \forall x \in X$$

(21)

where $\pi^k(x)$ is the current policy at $k$-step iteration, and $V^k(x)$ is the state value to be solved under policy $\pi^k(x)$. In the third step, PIM computes an improved policy by minimizing (22):

$$\pi^{k+1}(x) = \arg \min_{\pi} \mathbb{E}_{\hat{\xi}_k} \left\{ l(x', \pi(x)) + \gamma V^k(x') \right\}$$

(22)

where $\pi^{k+1}(x)$ is the new policy. The use of estimated $\hat{\xi}_k$ naturally embeds both analytical model and state-action data into RL, which is able to improve the accuracy of the additive stochastic uncertainty $\xi$ and $x'$ and achieve high convergence speed. The mixed RL algorithm is summarized in Algorithm 1.

Algorithm 1 Mixed RL algorithm

Initialize IBE parameters $\hat{\mu}_0 = \mu_M$ and $\hat{K}_0 = K_M$

Initialize state $x_0 \in \mathcal{X}$, $k = 0$

repeat

update distribution of $\hat{\xi}_k$ and mixed model with $\xi_k^D$ by IBE (20)

PEV with mixed model:

$$V^k(x) = \mathbb{E}_{\hat{\xi}_k} \left\{ l(x', \pi^k(x)) + \gamma V^k(x') \right\}$$

PIM with mixed model:

$$\pi^{k+1}(x) = \arg \min_{\pi} \mathbb{E}_{\hat{\xi}_k} \left\{ l(x', \pi(x)) + \gamma V^k(x') \right\}$$

$k = k + 1$

until $|V^{k+1} - V^k| \leq \epsilon$ and $|\pi^{k+1} - \pi^k| \leq \epsilon$

B. Recursive Stability and Convergence Under Fixed $\hat{\xi}$

In this section, we prove the recursive stability and convergence under fixed additive uncertainty $\hat{\xi}$.

1) Recursive stability: Recursive stability means $\pi_k$ can stabilize the plant so long as $\pi_{k-1}$ can. We call the closed-loop stochastic system is stable in probability, if for any $\epsilon > 0$, the following equality holds,

$$\lim_{x_0 \to 0} P \left( \sup_{t \geq 0} \|x_t\| \geq \epsilon \right) = 0$$

(23)

Lemma 1 (Lyapunov stability criterion [20]): If there exists a positive definite Lyapunov sequence $\{g(x_t)\}$ on $N \times \mathbb{R}^n$, which satisfies

$$\mathbb{E} \left\{ g(x_{t+1}) \right\} \leq g(x_t)$$

(24)

then the stochastic system is stable in probability, where $g(\cdot)$ is a continuous function, and $g(x_0) < \infty$.

Next, we prove the recursive stability criterion for mixed RL algorithm under fixed $\hat{\xi}$ using Lemma 1.

Theorem 1 (Recursive stability theorem): For any step $k$ in mixed RL, $\pi_{k+1}$ is stable in probability if $\pi^k$ is stable in probability and the discount factor $\gamma$ is selected appropriately under the mixed model.
Proof: Since \( u^{k+1} \) is optimal for “weak” Bellman equation, and \( u^k \) is non-optimal for \( k + 1 \) step value, we have:

\[
\mathbb{E}_\xi \{ l(x', u^{k+1}) + \gamma V^k(x') \} \leq V^k(x) \tag{25}
\]

where \( x' \) is the next state with \((x, u^{k+1})\) under the mixed model, and \( x'_{\text{opt}} \) is the next state with \((x, u^k)\). Therefore,

\[
V^k(x) \geq \mathbb{E}_\xi \{ V^k(x') + l(x', u^{k+1}) - (1 - \gamma)V^k(x') \} \tag{26}
\]

Since \( \pi^k \) is stable in probability, \( V^k(x) \) is bounded, thus, \( V^k(x') \) is bounded. Considering the fact that \( l(\cdot, \cdot) \) and \( V^k(\cdot) \) is positive definite function, \( 1 - \frac{l(x', u^{k+1})}{V^k(x')} < 1 \) holds, except for \((x', u^{k+1}) = (0, 0)\) which is stable in probability naturally.

We choose a proper \( \gamma \) to satisfy:

\[
l(x', u^{k+1}) - (1 - \gamma)V^k(x') \geq 0 \tag{27}
\]

1 - \( \frac{l(x', u^{k+1})}{V^k(x')} \leq \gamma < 1 \]

Therefore, \( V^k(x) \) is monotonically decreasing w.r.t time \( t \) with approximate \( \gamma \), i.e.,

\[
V^k(x) \geq \mathbb{E}_\xi \{ V^k(x') \} \tag{28}
\]

In short, \( \pi^{k+1} \) is stable in probability.

2) Convergence of mixed RL: The convergence property describes whether the generated policy, \( \pi^k \), can converge to the optimum \( \pi^* \) under the mixed RL. Here, we prove the convergence of mixed RL algorithm under fixed \( \xi^* \).

Theorem 2 (State value decreasing theorem): For any \( \forall x \in \mathcal{X} \) under the additive stochastic uncertainty \( \xi^* \), \( V^k(x) \) is monotonically decreasing with respect to \( k \), i.e.,

\[
V^k(x) \geq V^{k+1}(x), \forall x \in \mathcal{X} \tag{29}
\]

Proof: The key is to examine (except for \((0, 0)\))

\[
V^k = V^{k+1} \geq V^k \geq \cdots \geq V^{k+1} = V^{k+1} \tag{30}
\]

At each RL iteration, we initialize \( k + 1 \) step value function by \( V^{k+1}(x) = V^k(x) \). The first PEV iteration for \( \pi^k \) is

\[
V^{k+1}_1(x) = \mathbb{E}_\xi \{ l(x', u^{k+1}) + \gamma V^0(x') \} = \mathbb{E}_\xi \{ l(x', u^{k+1}) + \gamma V^k(x') \} \tag{31}
\]

With respect to (25), we know

\[
V^k(x) \geq V^{k+1}_1(x), \forall x \in \mathcal{X} \tag{32}
\]

For following PEV iterations, we need to reuse the inequality (32):

\[
V^{k+1}_1(x) = \mathbb{E}_\xi \{ l(x', u^{k+1}) + \gamma V^k(x') \} \geq \mathbb{E}_\xi \{ l(x', u^{k+1}) + \gamma V^{k+1}_1(x') \} \tag{33}
\]

Similarly, \( V^{k+1}_2(x) \) is a monotonically decreasing sequence and bounded by 0 for \( V^{k+1}_j(x) \geq 0 \) always holds. Finally, \( V^{k+1}_j(x) \) will converge

\[
\lim_{j \to \infty} V^{k+1}_j(x) = V^{k+1}_\infty(x) = V^{k+1}(x) \tag{34}
\]

So we have \( V^k(x) \geq V^{k+1}(x) \).

C. Recursive Stability and Convergence Under Varying \( \xi^k \)

In this section, we discuss the recursive stability and convergence under varying additive uncertainty \( \xi^k \), and propose the sufficient condition by designing an upper bound for the differences between \( \xi_k \) and \( \xi^k_{k+1} \).

Under \( \xi_k \), the self-consistency condition is

\[
V^k(x) = \mathbb{E}_{\xi_k} \{ l(x', u^k) + \gamma V^k(x') \} \tag{35}
\]

Since \( u^k_{k+1} \) is the optimal action with respect to \( V^k(x) \) of in the k-th iteration, we have

\[
\mathbb{E}_{\xi_k} \{ l(x', u^k_{k+1}) + \gamma V^k(x') \} \leq V^k(x) \tag{36}
\]

which is the key inequality in the proof in section IV-B.

However, when \( \xi \) is updated from \( \xi_k \) to \( \xi^k_{k+1} \), the variation of \( \xi \) should be bounded in the interest of stability and convergence. Here, we give the sufficient condition of recursive stability and convergence under varying \( \xi \), that is, the maximum variation condition (MVC) of the additive stochastic uncertainty (38).

Define \( h(x, u^k, \xi) \) as the expected cumulative cost under the additive stochastic uncertainty \( \xi \),

\[
h(x, u^k, \xi) = \mathbb{E}_{\xi} \{ l(x', u^k) + \gamma V^k(x') \} \tag{37}
\]

Theorem 3 (Sufficient condition for recursive stability and convergence): For any step \( k \) in mixed RL, \( \pi^{k+1} \) is recursive stable and \( V^k(x) \) is monotonically decreasing with respect to \( k \), if the following MVC is satisfied

\[
h(x, u^k_{k+1}, \xi_{k+1}) - h(x, u^k_{k+1}, \xi_k) \leq e_k(x) \tag{38}
\]

where \( e_k(x) \) is the decrease of cumulative cost after PIM,

\[
e_k(x) = h(x, u^k_{k+1}, \xi_k) - h(x, u^k_{k+1}, \xi_k) \geq 0 \tag{39}
\]

The MVC requires that the change of \( \xi_k \) has less impact on the cumulative cost calculation than PIM in the last iteration.

Proof: Since \( h(x, u^k_{k+1}, \xi_k) \geq 0 \), when MVC is satisfied, \( h(x, u^k_{k+1}, \xi_{k+1}) \leq h(x, u^k_{k+1}, \xi_k) \), thus, we have

\[
\mathbb{E}_{\xi_{k+1}} \{ l(x', u^k_{k+1}) + \gamma V^k(x') \} \leq \mathbb{E}_{\xi_k} \{ l(x', u^k_{k+1}) + \gamma V^k(x') \} \tag{40}
\]

Subsequently, recursive stability theorem (41) and state value decreasing theorem (42) under varying \( \xi \) can be proved similarly to section IV-B

\[
V^k(x) \geq \mathbb{E}_{\xi_{k+1}} \{ V^k(x') \} \tag{41}
\]

\[
V^k(x) \geq V^{k+1}(x) \tag{42}
\]

Next, we first present Lemma 2 that will be used for the convergence analysis of IBE, then we prove the MVC is satisfied with probability one.

Lemma 2 (Convergence criterion of Bayesian estimation [21]): In Bayesian estimation, if the empirical data \( D \) and the parameter’s prior distribution obey Gauss distribution and the covariance matrix of prior distribution is full rank, then
the estimation result $\hat{\mu}$ and $\hat{\kappa}$ will converge to the sample’s mean and covariance asymptotically.

**Theorem 4** (MVC is satisfied with probability one criteria): The MVC is satisfied with probability one after sufficient iterations, with the assumption that the IBE converges faster than PIM and PEV.

**Proof:** Using Kolmogorov strong law of large numbers [22], we have

$$\lim_{k \to \infty} P \left\{ \frac{1}{k} \sum_{j=1}^{k} \xi_j^D = \mu \right\} = 1$$

(43)

$$\lim_{k \to \infty} P \left\{ \frac{1}{k} \sum_{j=1}^{k} (\xi_j^D - \mu) (\xi_j^D - \mu)^T = \kappa \right\} = 1$$

where $\varepsilon$ and $\delta$ are arbitrary small positive constants, $\mu$ and $\kappa$ are the true mean and covariance of $\xi$. Thus, using Lemma 2 and (43), we know that, when $k \to \infty$, $\hat{\mu}_k$ and $\hat{\kappa}_k$ converges to $\mu$ and $\kappa$ in probability one [21], i.e.,

$$\hat{\mu}_k \xrightarrow{p} \mu, \quad \hat{\kappa}_k \xrightarrow{p} \kappa$$

(44)

Since $\hat{\mu}_k \xrightarrow{p} \hat{\mu}_{k+1} \xrightarrow{p} \mu$, $\hat{\kappa}_k \xrightarrow{p} \hat{\kappa}_{k+1} \xrightarrow{p} \kappa$, and both $p(\hat{\xi}_k)$ and $p(\hat{\xi}_{k+1})$ obey Gaussian distribution, the KL-divergence between $p(\hat{\xi}_k)$ and $p(\hat{\xi}_{k+1})$ converge to 0 with probability one [23], i.e.,

$$\lim_{k \to \infty} P \left\{ D_{KL} \left( p(\hat{\xi}_k), p(\hat{\xi}_{k+1}) \right) = 0 \right\} = 1$$

(45)

$$\Leftrightarrow \mathbb{E} \left\{ p(\hat{\xi}_k) \log \frac{p(\hat{\xi}_k)}{p(\hat{\xi}_{k+1})} \right\} \xrightarrow{p} 0 \Leftrightarrow \frac{p(\hat{\xi}_k)}{p(\hat{\xi}_{k+1})} \xrightarrow{p} 1$$

Thus, we have

$$\int \left( p(\hat{\xi}_k) - p(\hat{\xi}_{k+1}) \right) \left\{ I(x', u) + \gamma V^k(x') \right\} d\xi \xrightarrow{p} 0$$

(46)

$$h(x, u, \hat{\xi}_{k+1}) - h(x, u, \hat{\xi}_k) \xrightarrow{p} 0$$

Since $e_k(x) \geq 0$, when $k \to \infty$, the MVC (38) holds with probability one, i.e.,

$$\lim_{k \to \infty} P \left\{ h \left( x, u^{k+1}, \hat{\xi}_{k+1} \right) - h \left( x, u^{k+1}, \hat{\xi}_k \right) \leq e_k(x) \right\} = 1$$

(47)

In general, MVC indicates that the excessive difference between $\hat{\xi}_{k+1}$ and $\hat{\xi}_k$ should be avoided. In mixed RL, we update the distribution of the additive stochastic uncertainty by Bayesian estimation. As shown in Fig. 3, if a single data batch has large deviation from the total data, the Bayesian estimator can reduce the deviation between the posterior distribution and the total data distribution by introducing appropriate prior distribution of parameters.

V. MIXED RL WITH PARAMETERIZED FUNCTIONS

For large state spaces, both value function and policy are parameterized in mixed RL, as shown in (48). The parameterized value function with known parameter $w$ is called the “critic”, and the parameterized policy with known parameter $\theta$ is called the “actor” [24].

$$V(x) \equiv V(x; w)$$

$$u \equiv \pi(x; \theta)$$

(48)

The parameterized critic is to minimize the average square error (49) in PEV, i.e.,

$$J_{\text{critic}} = \mathbb{E}_{\xi} \left\{ \frac{1}{2} \left( l(x', u_{\theta}) + \gamma V^k(x'; w) - V^k(x; w) \right)^2 \right\}$$

(49)

The semi-gradient of the critic is

$$\frac{\partial J_{\text{critic}}}{\partial w} = \int p(x') \left( V^k(x; w) - V_{\text{target}} \right) \frac{\partial V^k(x; w)}{\partial w} dx'$$

(50)

where $V_{\text{target}} = l(x', u_{\theta}) + \gamma V^k(x')$ and $x' = f(x, u_{\theta}) + \hat{\xi}$. The parameterized actor is to minimize the “weak” Bellman condition, i.e., to minimize the following objective function,

$$J_{\text{actor}} = \mathbb{E}_{\xi} \left\{ l(x', u_{\theta}) + \gamma V^k(x') \right\}$$

$$= \int \left[ l(x', u_{\theta}) + \gamma V^k(x') \right] p(x'; u_{\theta}) dx'$$

(51)

$$p(x'; u_{\theta}) \sim N \left( f(x, u_{\theta}) + \hat{\mu}, \hat{\kappa} \right)$$

where $\hat{\mu}$ and $\hat{\kappa}$ are the mean and covariance of $\hat{\xi}$. The gradient of $J_{\text{actor}}$ is calculated as follows,

$$\frac{\partial J_{\text{actor}}}{\partial \theta} = \int \left\{ \left[ l(x', u_{\theta}) + \gamma V^k(x') \right] \frac{\partial p(x'; u_{\theta})}{\partial \theta} + \frac{\partial l(x', u_{\theta})}{\partial \theta} p(x'; u_{\theta}) \right\} dx'$$

(52)

In essence, the parameterized method is called generalized policy iteration (GPI). Different from the traditional policy iteration, PEV and PIM each has only one step in GPI, which greatly improves the computational efficiency when RL is combined with neural network.

Since in each GPI cycle, the gradient descent of PIM is only carried out once, the maximum variation condition (MVC) may not be satisfied. We propose a Adaptive GPI (AGPI)
method to solve this problem. In every iteration, we check whether the PIM results satisfy MVC. If not, the algorithm will continue the gradient descent steps in PIM until the MVC is satisfied or when the maximum internal circulation step is reached. Subsequently, the mixed RL algorithm with parameterized Adaptive GPI (AGPI) is summarized in Algorithm 2.

Algorithm 2 Mixed RL with parameterized value and policy

Initialize IBE parameters $\mu_0 = \mu_M$ and $K_0 = K_M$
Initialize network weights $\theta_0$ and $w_0$, choose appropriate learning rates $\alpha$ and $\beta$, $k = 0$
repeat
update distribution of $\hat{q}_k$ and mixed model with $\xi_k^D$ by IBE (20)
update Critic with $\hat{q}_k$
$w^{k+1} = w^k - \alpha \frac{\partial J_{GPI}}{\partial w}$
update Actor with $\hat{q}_k$
$\theta^{k+1} = \theta^k - \beta \frac{\partial J_{Actor}}{\partial \theta}$
Set $j = 0$
repeat
update policy net, $j = j + 1$
until MVC (38) is satisfied or $j = j_{max}$
$k = k + 1$
until $|V^{k+1} - V^k| \leq \epsilon$ and $|\pi^{k+1} - \pi^k| \leq \epsilon$

VI. NUMERICAL EXPERIMENTS

We consider a typical optimal control problem of stochastic non-affine nonlinear systems, i.e., the combined lateral and longitudinal control of an automated vehicle with stochastic disturbance (i.e., the influence of small road slope and road bumps). The vehicle is subjected to random longitudinal interference force $F_{dis}$ in the tracking process and the vehicle dynamics is shown in (53) [25].

$$\dot{x} = \begin{bmatrix} F_{yf} \cos \delta + F_{yr} & -v_x r \\ \frac{F_y m}{v_y} \cos \delta - b F_{yr} & a_x + v_y r - \frac{F_y m}{v_y} \sin \delta + F_{yr} \\ v_x \sin \phi + v_y \cos \phi \end{bmatrix}$$

(53)

where the state $x = \begin{bmatrix} v_y & r & v_x & \phi & y \end{bmatrix}^T$, $v_y$ is the lateral velocity, $r$ is yaw rate, $v_x$ is the difference between longitudinal velocity and desired velocity, $\phi$ is the yaw angle, and $y$ is the distance between vehicle’s centroid and the target trajectory. For the control input $u = [\delta, a_x]^T$, where $\delta$ is the front wheel angle and $a_x$ is the longitudinal acceleration. The $F_{yf}$ and $F_{yr}$ are the lateral tire forces of the front and rear tires respectively, which are calculated by the Fiala tire model [26]. In the tire model, the tire-road friction coefficient $\mu$ is set as 1.0. The front wheel cornering stiffness and rear wheel cornering stiffness are set as 88000 $N/\text{rad}$ and 94000 $N/\text{rad}$ respectively. The mass $m$ is set as 1500 kg, the $a$ and $b$ are the distances from centroid to front axle and rear axle, and set as 1.14 $m$ and 1.40 $m$ respectively. The polar moment of inertia $I_z$ at centroid is set as 2420 $N/\text{rad}$.

For control performance, we test the policies calculated by three methods in the double lane change task. As shown in Fig. 5, all three policies stably tracked the target trajectory, but with different control error. In fact, as shown in Fig. 6, the mixed RL has the minimum longitudinal speed error, since

![Fig. 4. Convergence rate comparison between mixed RL, model-driven RL, and data-driven RL.](image-url)
it enables the vehicle to decelerate rapidly at sharp turns and adjust back appropriately after passing the turns. In contrast, due to the model error, the model-driven RL has higher speed error and its deceleration when making turns is insufficient. Due to the slow convergence, the data-driven RL generates a poor solution and has the largest speed error. The mixed RL also outperforms the other two benchmark methods in terms of the lateral position error. As shown in Fig. 7, the mixed RL has the minimum steady-state lateral position error, while data-driven RL has the largest lateral position error and frequent speed fluctuation.

The mean absolute errors of three methods are compared in Table I. The longitudinal speed error of mixed RL is 77.41% less, and the lateral position error is 33.77% less than the data-driven RL. Besides, the longitudinal speed error of mixed RL is 58.82% less, and the lateral position error is 15.64% less than the model-driven RL.

In summary, mixed RL exhibits the fastest convergence speed during the training process and the greatest control performance in double lane change task. The model-driven RL has similar convergence speed as the mixed RL, but has higher control error due to the model error. The data-driven RL has the slowest convergence rate and the largest control error, due to the difficulties in finding the optimal policy only by state-action data.

VII. CONCLUSION

This paper proposes a mixed reinforcement learning approach with better performances on convergence speed and policy accuracy for non-linear systems with additive Gaussian uncertainty. The mixed RL utilizes an iterative Bayesian estimator to accurately model the environmental dynamics by integrating the designer’s knowledge with the measured state transition data. The convergence and recursive stability of learned policy were proved via Bellman’s principle of optimality and Lyapunov analysis. It is observed that mixed RL achieves faster convergence rate and more stable training process than the data-driven counterpart. Meanwhile, mixed RL has lower policy error than model-driven counterpart since the environmental model is refined iteratively by Bayesian estimation. The benefits of mixed RL are demonstrated by a double-lane change task with an automated vehicle. The potential of mixed RL in more general environmental dynamics and non-Gauss uncertainties will be investigated in the future.

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