

Multi-Agent Reinforcement Learning Simulation for Multi-Joined Robot

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Abstract: This paper describes a multi-agent influence learning approach and reinforcement learning adaptation to it. This learning technique used for distributed, adaptive and self-organizing control in multi-agent system. This technique is quite simple and uses agent's influences to estimate learning error between them. The best influences is rewarded via reinforcement learning which is well proven learning technique. As will show, this learning rule supports positive-reward interactions between agents and does not require any additional information than standard reinforcement learning. This technique produces optimal behavior's patterns with fast convergence.

Keywords: Multi-Agent Learning, Reinforcement Learning, Influence Learning, Simulation,

1. INTRODUCTION

Machine learning being explored an important component in multi-agent systems (MAS). For example, many application domains are envisioned in which teams of software agents or robots learn to cooperate amongst each other and with human beings to achieve global objectives [1]. Learning may also be essential in many non-cooperative domains such as economics and finance, where classical game-theoretic solutions are either infeasible or inappropriate. Teams of agents have the potential for accomplishing tasks that are beyond the capabilities of a single agent. An excellent and demanding example of multi-agent cooperation is in robot soccer. At the same time, Multi-Agent learning (MAL) poses significant theoretical challenges, particularly in understanding how agents can learn and adapt in the presence of other agents that are simultaneously learning and adapting [2,3].

2. REINFORCEMENT LEARNING

Reinforcement learning is an approach to artificial intelligence that emphasizes learning by the individual from its interaction with its environment that produces optimal behavior [4]. It is often used as one of the control techniques, especially for learning autonomous agents in unknown environment. It emerged at the intersection of dynamic programming, machine learning, biology, studies the reflexes and reactions of living organisms: reflex theory, animal cognition [5,6]. RL is highly popular for learning autonomous agents, for example autonomous robotics, negotiating agents and so on. The math foundation of RL is Markov Decision Pprocess (MDP), so it widely used for learning in game theory, e.g. TD-Gammon [10].

The core of all most Reinforcement Learning methods is a Temporal Difference (TD) learning [4-9]. Temporal Difference technique measures the inconsistency between difference of quality for two actions done in some state and received reward, shows expectation of agent.

Agent execute action a in particular state s , goes to

next state s' and receives reward r as a feedback of recent action. During learning agent try to select the best action in some state (best action usually more rewarded in future). Visually, iteration of RL-agent on MDP is shown at Fig. 1.

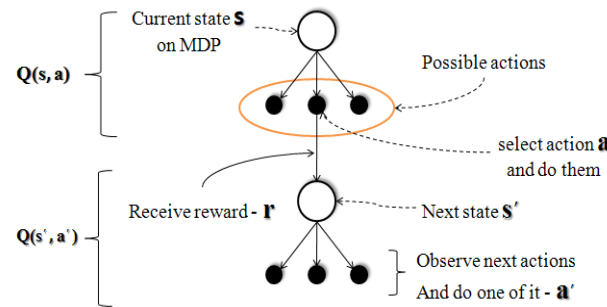


Fig. 1 - One iteration of Reinforcement learning.

Where α - learning rate, γ - discount factor, determines the importance of future rewards.

Learning goal is to approximate Q -function (1), e.g. finding true Q -values of Q -function for each action in every state. Formula 1 shows SARSA learning rule. Estimated in square brackets value is Temporal Difference error.

$$\Delta Q(s, a) = \alpha[r + Q(s', a') - Q(s, a)] \quad (1)$$

The natural extension of standard RL algorithm is usage eligibility traces to remember previously visited states. Eligibility trace is a temporary records of the occurrence of an event, such as the visiting of a state or the taking of an action [4]. At every time step, when a TD error occurs, only the eligible states or actions are updated.

$$\Delta Q(s, a) = \alpha[r + Q(s', a') - Q(s, a)]e(s) \quad (2)$$

$$e(s) = \begin{cases} \lambda \gamma e(s) & \text{if } s \neq s', \\ \lambda \gamma e(s) + 1 & \text{otherwise} \end{cases} \quad (3)$$

Formula (2) called for every previously visited state if $e(s) > 0$, where $e(s)$ - is a eligibility value, λ - is a eligibility discount factor, decay in time past eligibilities.

Reinforcement Learning works well in case of one agent. In case of multi-agents system Reinforcement Learning update rule should be updated for better convergence to reduce several limitations [2, 3, 4, 6]. It is exponentially growing state-action space depending on number of agents, curse of dimensionality, and decentralization of learning process.

3. MULTI AGENT REINFORCEMEN LEARNING

In many articles multi-agent reinforcement learning (MARL) has shown in context of game theory for founding Nash equilibrium point for group of agents. Terms 'coordination' and 'cooperation' used in Multi-Agent Systems is well known in game theory (e.g. zero sum stochastic games and common-payoff). There are several models of Game Theory approaches to multi-

agent learning. Works [1,12,13] provided generalized view to this approach, and [14] pointed, that Multi-Agent learning is a different kind of machine learning and still open question. In robotics, multi-agent reinforcement learning has been applied to teams of robots with Q-learning as the algorithm of action choice.

In previous papers [15-17] we propose *Influences Reinforcement Learning* as a simple reinforcement learning technique for distributed multi-agent system with local update rule and fast convergence.

Influences Reinforcement Learning (I-RL) based on assumption if some problem solved cooperatively by agents so their learning process is related to each other and influences between agents can be used to estimate error value between agents. In this case, actions from one agent may be directed to another agents and change their states.

Let's see to interconnected agents A and B. Agent A at state s_a execute action a over agent B, and set it into new state s_b . Agent in new state B select action b and execute it somewhere (on another agent, or on environment). This situation is shown at Fig. 2.

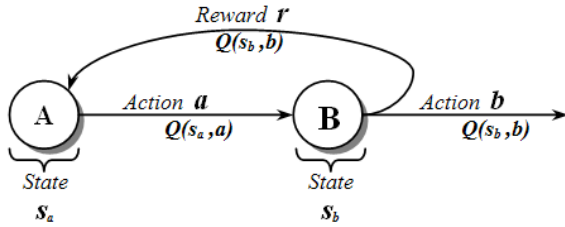


Fig. 2 - Influences between two agents. Reinforcement learning view.

Actions a and b has their Q-values $Q(s_a, a)$ and $Q(s_b, b)$ respectively. After executing action and receiving reward agent B can sent feedback to A. This feedback include Q-value $Q(s_b, b)$ and reward r as a response to action a . Receiving this feedback agent A can calculate Temporal Difference error between them and agent B and learn using standard RL technique. Agent A update their Q-value $Q(s_a, a)$ corresponding to action a using formulas (4, 5).

$$\delta_{AB} = r + \gamma Q(s_b, b) - Q(s_a, a) \quad (4)$$

$$\Delta Q(s_a, a) = \alpha \delta_{AB} \quad (5)$$

Formula (4) defines a *influence error* as a *temporal difference error* between agent A and B. Expression $r + \gamma Q(s_b, b)$ - is a feedback from agent B.

The most one important change in I-RL is that we suppose a $Q(s_b, b)$ - is a "future" Q-value of agent A, and in this case (5) is equal to (1). Using this update rule, the best influences from A to B will be more rewarded. In the end, agent A can build the optimal interaction policy for agent B. Feedback between agents included into update rule produces coherence of their behaviors. The advantage of this rule is simplicity and all single-agent RL algorithms can be used without serious changes.

Including eligibility traces into agent interactions we can reduce decentralization of learning process and update coherent influences more than between two agents. In influence trace we store history (set) of agent influences to each other, as number of I-RL procedures.

For example, let's see to more complicated and

distributed example from previous chapter. Introduce one more agent C. This situation is shown at Fig. 3.

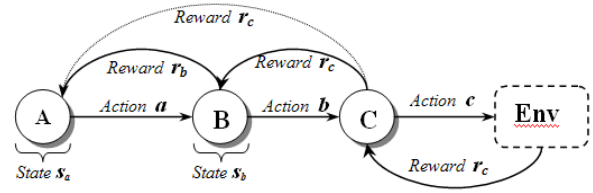


Fig. 3 - Influences between two agents (common case). Reinforcement learning view.

Agents interact in following scenario:

1. Agent A acts to agent B with $Q(s_a, a)$. Agent B goes to state s_b .
2. Agent B acts to agent C with $Q(s_b, b)$. Agent C goes to state s_c .
3. Agent C acts with action c to environment *Env* and receive their reward.
4. Agent C receive reward r_c and send it to all agents who influence to it.
5. Agent's B receive reward r_c for b and learn. Also, agent B can calculate their own reward r_b and feedback it to agent A.
6. Agent A receive all reward's and learn.

As we can see at fig. 3, there are direct interaction between A-B, and B-C, and indirect interaction between A and C. Using influence trace we can learn and update these indirect interactions.

For this purposes we introduce parameter *influence value* $i(d)$ into update rule, where d is a distance between agents. This parameter shows how far away *structurally* produced influence to this agent. For direct interactions d is equal to 0; for indirect interaction $d > 0$, depending on how many intermediate influences done between indirect agents. For direct agent's interactions A-B and B-C the influence distance d equal to 0. For indirect interaction A-C influence distance is equal to 1. If we introduce one more agent D after C, so influence distance between A-D will be 2, and so on. The update rule changed as follows:

$$\delta_{AC} = r_c + \gamma Q(s_c, c) - Q(s_a, a) \quad (6)$$

$$\Delta Q(s_a, a) = \alpha \delta_{AC} i(d) \quad (7)$$

$$i(d) = \lambda^{d-1} \quad (8)$$

Where δ_{AC} - is a influence error between agent A and C, λ - is a coefficient of influence discount factor.

Influence value $i(d)$ is depends from discount factor λ and reduced with increasing influence distance between agents. If $\lambda = 1$, then all influences will be updated with full power. If $\lambda = 0$ only direct interactions will be updated. If $0 < \lambda < 1$ then indirect interactions will be updated with decay.

4. MODEL OF MULTI-JOINED ROBOT

Multi-Joined Robot (MJR) learning task is a simple decentralized model, which simulate robot arm with N-degrees of freedom, where N - is a number agents in MAS. Every segment - is an intellectual agent learned via Reinforcement Learning. The goal of experiment is to learn MJR reach some target point. This problem requires synchronization of local agent behaviors to achieve one common goal.

MJR contains one root segment **R**, several

intermediate segments S_1, S_2, \dots, S_m , and one terminal segment T connected into chain from R to T (Fig. 6). Every segment, excluding terminal, can rotate at full circle (360°) all next segments. At one time step each segment, excluding terminal, can rotate all next segments at 5° to left or right, or do nothing.

First acts root segment R , then first intermediate S_1 , then second S_2 and so on, until S_m . Root segment can't move, can't be moved and don't change their position. Terminal segment verify reaching the target and receive actions from previous segments that change their own position.

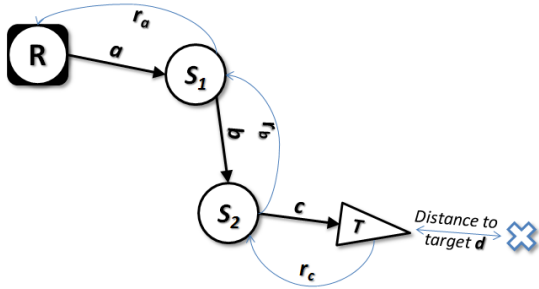


Fig. 4 - Multi-Joined Robot with 4 segments R, S_1, S_2, T .

a, b, c - Agent actions. r_a, r_b, r_c - Feedback reward corresponds to actions.

Used next learning procedure (one training start):

1. MJR moved to initial position.
2. Every segment selects and executes action in order to structure of MJR. States of all next agents are changed.
3. Terminal segment calculate distance to target point.
4. If target is reached then MJR count grand-prix reward and learned. Go to 1.
5. Else, terminal segment produce feedback reward for previous agent to learn it. Feedbacks are propagated into MJR, so agents learn via RTD until root segment will be reached.
6. If simulation time is ended (1000 simulation steps) go to 1. If average RTD-Error (7) lower than limit value, then learning is over.
7. Next time step. Go to 2

Reinforcement Learning parameters include: α (learning rate) = 0.05~0.1; γ (discount factor) = 0.7; λ (eligibility discount factor) = 0.7~0.99, d (influence discount factor) = 0.5~0.7

5. EXPERIMENTAL RESULTS

Earlier, behavior patterns in multi-agent systems were researched at [13,14]. Simulation of MJR behavior shows intension to find optimal structure of segments for the robot. During learning synchronization of behaviors between segments (successful learning) produces optimal interactions from which robot can reach the target.

In our experiments was used two basic reinforcement learning technique: *SARSA*, described above, and *Q-Learning*, using the following update formula:

$$\Delta Q(s, a) = \alpha [r + \gamma \max_{a' \in A} Q(s', a') - Q(s, a)] \quad (9)$$

One of extensions of *Q-Learning with eligibility traces* is known as *Wankins-Q(λ)*, where λ - it is a eligibility discount factor. This learning rule was also used in experiments.

Convergence. In experiments we used MJR with 5 active segments. It is good compromise between model

complexity and decentralization of agent actions. The case of MJR with more than 5 segments is described below. The normal convergence process using *Q-Learning* update rule illustrated at fig 5.

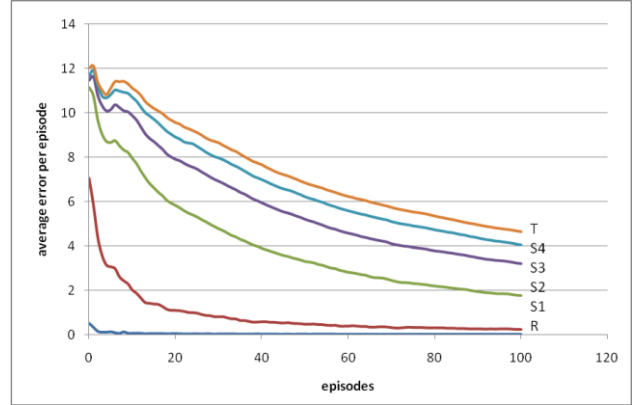


Fig. 5 - Average I-RL error per episode for every segment.

As been shown, there are direct dependencies between agent's actions and errors. Every next segment can be placed at more states (has biggest state-action space), than others, and its error value become higher.

Learning. The MJR learning contains with two parts. First part - it is a learning of optimal behavior. In this part robot explore the world trying to create (learn) best behavior policy. The second part uses found best behavior policy to finding optimal structure of MJR. Using this structure, MJR should reach target in shortest way with minimum number of actions. Usually, the better strategy is rotating with minimum segments reconfigurations. In this case only one segment does actions.

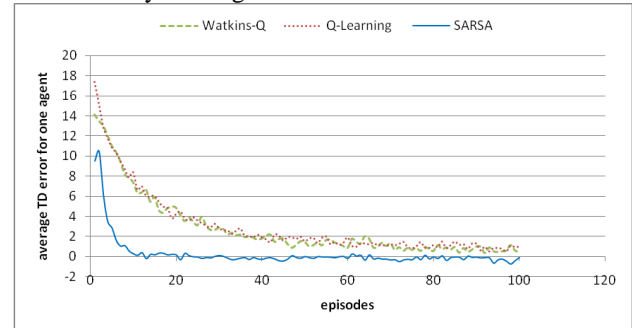


Fig. 6 - SARSA, Q-Learning and Watkins-Q(λ) I-RL convergence comparison.

Learning decentralization. Quality of convergence depends from number of segments. If MJR have more than 6 segments then probability of convergence is much lower. The main problem in this case is decentralization of agent actions. Fig. 6-a shows situation where actions in the beginning of robot not synchronized with actions in the end of robot. The memory techniques, such as eligibility traces, are not enough for MJR containing more 7 step-by-step interactions between agents, and new techniques of learning for reducing complexity should be used.

SARSA algorithm show fast convergence but worse synchronization properties. *SARSA(λ)* with eligibility traces show more smooth behavior in coordination of agent actions.

Q-Learning shows longest, but stable convergence with better synchronization and behavior properties. *Q-Learning* has better approximation of *Q-Function* which

can produce better actions for agent.

6. CONCLUSION

This work suggests new approaches to Multi-Agent Reinforcement Learning named Influence Reinforcement Learning. This technique was designed to change standard Reinforcement Learning model in a best essential way to Multi-Agent Learning. Using I-RL we can apply RL model between agents locally.

This technique was used to produce observed behavior patterns during learning multi-joined robot. This patterns was classified as direct reaching, partial rotation and synchronization and rotation around fixed points. Fixed point rotation it is an optimal pattern with minimum number of required actions to reach the target. The state-action space should be explored by learning algorithm to find an optimal fixed point, to build optimal MJR structure.

The I-RL learning has two known limitations. One is decentralization problem for long indirect influences, and second one is problem of agent influences insurance. The agent should be sure, that received influences as much optimal, as possible. It is a guarantee of I-RL algorithm convergence. The future experiments and extension if I-RL is needed.

7. ACKNOWLEDGMENTS

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