Sequential decision making under the presence of uncertainties is frequently modeled by Markov decision processes (MDPs). In practical applications, however, the parameters of MDPs are often not exactly known, they are usually estimated, and therefore, there may be parameter uncertainties, as well. In the presentation, first, I consider the case when the transition-probability function is fixed, but uncertain, viz., we do not know what it is, we only know that it belongs to a given uncertainty set. I propose an efficient robust convex optimization based approach to handle this problem. Then, I analyze the case, when the transition-probability and the immediate-cost functions are uncertain in a way that they may vary from time to time, provided that the accumulated changes remain asymptotically bounded. I investigate the possibility of applying stochastic iterative algorithms (SIAs) in this kind of changing environments. I present a generalized stochastic approximation theorem for SIAs with time-dependent update operators. Afterwards, I apply this theorem to deduce a convergence theorem for value function based reinforcement learning (RL) methods working in changing MDPs. Finally, I illustrate the results through variants of classical RL algorithms as well as numerical experiments.

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