Autonomous navigation is a critical aspect of operations performed by mobile robots in numerous applications such as domestic vacuum cleaning, autonomous vehicle driving, robot-based warehouse inventory management, and, critical applications such as unmanned search and rescue, and extraterrestrial exploration. The main problem in autonomous navigation is to enable a robot to determine a collision free path between its start and goal locations while reducing the amount of energy and/or time required to move along that path, and, while satisfying constraints such as maintaining a minimum clearance with obstacles along the path. Autonomous navigation is further complicated in most real-life situations as robot's sensors have limited range and the robot might not have access to an a priori or accurate map of the entire environment. Consequently, robots have to make navigation decisions based on the limited information from the environment in their immediate vicinity perceived through their sensors. Unfortunately, making decisions with limited environment information can either require time- and computationally-intensive, motion planning calculations to navigate efficiently, or, result in time- and energy-wise inefficient navigation maneuvers if the robot uses naive motion planning techniques.

To address this robot navigation decision making problem in an efficient manner, we propose to use a machine learning technique called transfer learning which enables a robot to navigate efficiently in complicated environments by reusing its previous knowledge acquired from human demonstrations or through navigation in past environments. In this dissertation, we have proposed two techniques - the first technique uses a concept called experience-based learning that enables a robot to reuse learned navigation maneuvers from past environments to navigate in new environments, albeit with obstacle boundary patterns similar to those encountered in the past environments. In the second technique, we generalize this concept by relaxing the constraint that obstacle boundary patterns have to be similar and present the main technique of this dissertation called Semi-Markov Decision Processes with Uncertainty and Transfer (SMDPU-T). In the second part of this dissertation, we proposed three techniques to enhance the performance of the SMDPU-T algorithm from different aspects by utilizing inverse reinforcement learning, unsupervised learning and deep reinforcement learning. All the proposed techniques in this dissertation were implemented either on a simulated or a physical mobile, four-wheeled robot called Coroware Corobot or Turtlebot which showed that the robot using our proposed techniques could navigate successfully in new environments with previously un-encountered obstacle boundary geometries. Our experimental results on simulated robots within Webots simulator illustrate that SMDPU-T takes 24% planning time and 39% total time to solve same navigation tasks while, our hardware results on a Turtlebot robot indicate that SMDPU-T on average takes 53% planning time and 60% total time as compared to a recent, sampling-based path planner. As the final contribution of this dissertation, we extended the proposed path planning approach from a single robot to a multi-robot system with multiple ground robots, that are able to learn efficient navigation maneuvers across different environments from each others' past navigation experiences through a robot cloud-like infrastructure.

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