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（Summary）

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Machine learning approaches have recently been adopted for robot modeling and control, where robot skills are acquired and adapted from data generated by the robot while interacting with its environment through a trial-and-error process. This endows robots with the capabilities to adapt to changing and open-ended environments, by acquiring new skills and behaviors as their environments and demands change. Furthermore, as learning-based control techniques are capable of modeling complex systems, modern robots no longer have to be designed to simplify modeling but can be designed to suit various demands and environments.

Despite the success that learning-based approaches promise us, robot learning of new control skills remains one of the main challenges, especially for manipulators and humanoids, mainly due to their large and high-dimensional state and action spaces, as a large amount of data must be collected, requiring long training times. Furthermore, their physical embodiment allows only for a limited time for collecting training data.

In this thesis, we aim to accelerate robot learning of motor skills using knowledge transfer, where we re-use data generated by other pre-existing robots to accelerate learning for a new robot. The advantage of transferring raw data is that the knowledge transfer system will not restrict the robots to the same knowledge representations and thus the same type of learning algorithms. However, knowledge transfer across robots is fraught with many challenges, specifically due to the robots having different embodiments and physical characteristics.

We propose a transfer learning model, Local Procrustes Analysis, and algorithms for training it, to enable knowledge transfer across such robots with different embodiments and physical characteristics. We demonstrate the efficacy of our proposed model in accelerating learning of manipulator kinematics and dynamics. More specifically, we accelerate learning of sensorimotor mappings -- forward and inverse kinematics -- and online learning of inverse dynamics for manipulator trajectory tracking control. Moreover, we propose an approach that contributes towards robot learning from demonstrations that enables non-robotics-expert human users to transfer skills to robots, and demonstrate that our approach can be extended to allow robots to share knowledge acquired from a human.

Related work in robot learning from demonstration where human motions are adapted onto the robot body assume an accurate kinematic model of the robot is available, and they employ kinematic retargetting techniques. In the absence of this kinematic model, machine learning approaches seek to map data generated by the human teacher onto the space of the robot learner. However, the majority of the approaches transfer non-goal-directed tasks, such as dancing. In contrast, our approach transfers goal-directed tasks, where the robot

aims to perform a task typically with its end-effector, such as painting, welding, drawing, etc.

In transfer for online learning of inverse dynamics for manipulator trajectory tracking control, not a lot work is available. It has been shown that transfer for forward kinematics and inverse dynamics is possible between two manipulators with different dynamics and number of degrees-of-freedom. In this thesis, we developed an architecture for collecting training data for learning transfer models, and demonstrated the benefit of knowledge transfer in accelerating online learning of inverse dynamics for manipulator trajectory tracking.

Finally, we experimented with knowledge transfer for accelerating learning of sensorimotor mappings for developmental learning robots. In the single-robot case, exploration in the world is performed alone and the robot explores its own capabilities. In a multi-robot case, it may be beneficial for the robots to be able to share the knowledge they have acquired through their individual exploration. Such knowledge sharing has the potential to speed up development significantly and can allow more experienced or capable robots to impart their wisdom to others.

We explore knowledge transfer in the context of learning kinematics models, where an experienced robot shares its kinematic data with a new robot that is autonomously exploring its environment, in order to accelerate its learning process. Our preliminary results show that by sharing kinematic data across robots, the sensorimotor models of the new robot can converge faster and also achieve a higher performance compared to individual exploration from scratch, when allocated the same exploration time.

We validate our approaches using simulated robots, ranging from simple planar manipulator robots to more complex industrial manipulators and humanoids. Our results demonstrate that not only is transfer across robots possible, but it is also beneficial to accelerating learning for new robots based on data gathered by more experienced robots.