

Synthetic Robot Language Development

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Cooperating robots can benefit from communication. Our robots create their own adaptable synthetic robot languages (ASRLs). We have shown that robots can develop “basic”, context dependent, and compositional ASRLs using reinforcement learning techniques. (See (Yanco 1994) for a complete description of this work.)

We have demonstrated that the robots are able to develop ASRLs using two different reinforcement schemes: task-based reinforcement and individual reinforcement. In task-based reinforcement, the robots only receive positive reinforcement when the task is completed properly. This reinforcement method is preferable in situations where it can not be determined who performed the correct actions to reach the goal, but it is clear that the goal was reached. Individual reinforcement is better suited to tasks where it is clear which of the robots helped to reach the goal. This determination is used to give the robots that helped reach the goal good reinforcement while penalizing the robots that did not contribute toward the group goal. In our model, the robots are able to learn more quickly using the individual reinforcement, but at the expense of convergence. However, most tasks can not easily be decomposed to determine which members of the group acted correctly, and even for those tasks that can be easily decomposed, the overhead necessary to make the determination is often costly. While task-based reinforcement results in longer learning times, it only requires a one-bit decision in allocating reinforcement.

The basic ASRL is a simple one-to-one mapping of robot signals to robot actions. The development of this ASRL in simulation and with robots demonstrated that robots could learn to communicate and could adapt their language to changing circumstances.

Simulated robots have also created a context dependent ASRL. In a context dependent language, robot words can have different meanings depending on the

state of the world as perceived through sensor readings. For example, the robots could learn a command for *DO*, where they should *DO recharge* in the presence of a charging station, *DO gather* when sensors indicate that objects are present that should be collected, or *DO sleep* when the lights are turned out. The context dependent language requires shorter learning times than the basic experiment because the robots need to learn fewer ASRL signals.

The simulated robots have also developed a compositional ASRL. A compositional language combines words with ways for the words to be put together to form higher level concepts. For example, you have probably never read a sentence exactly like this one before; however, you are able to understand the sentence because you know the meanings of the words in this sentence and understand English grammar. In the basic ASRL, whenever the robots encounter a new sentence (or concept), they must start the learning process from scratch, even if the concept only varies slightly from a previously learned concept. In compositional ASRLs, the robots can use what they have already learned as they encounter new sentences containing old words. Therefore, the learning times for the compositional ASRL are dramatically faster than for both the basic ASRL and the context dependent ASRL.

Adaptable synthetic robot languages developed by the robots themselves have several advantages. They allow the robots to create languages that will be well-suited to specific tasks and to the capabilities of the robot hardware. ASRLs require less human involvement than pre-programmed robot languages. The robots are able to adapt to changing circumstances without outside assistance. In a dynamic environment where robots must work continuously without human assistance, adaptable synthetic languages are the communication method of choice.

References

- Yanco, H. A. 1994. Robot communication: issues and implementations. Master’s thesis, Massachusetts Institute of Technology. Also available as MIT-AI-TR 1478.

*This research is supported by the NSF under Professor Lynn Andrea Stein’s NSF Young Investigator Award No. IRI-9357761, Digital Equipment Corporation, the Gordon S. Brown Fund, and ARPA ONR contract N00014-91-J-4038. Any opinions, findings, conclusions or recommendations expressed in this material are those of the author and do not necessarily reflect the views of the NSF.