Introduction

In spite of rapid developments in computer hardware and software over the past few decades, there are many problems computers can't solve as good as people. Take, for example, CAPTCHA, "Completely Automated Public Turing test to tell Computers and Humans Apart". It is based on the fact that computers are not very good at recognizing distorted, covered, or partially erased images. Humans can do it easily. On one hand, people use this fact to their advantage in network authentication tasks. On the other hand, there are situations when people would want computers to be as intelligent as humans. An example of one area where an artificial intelligence would be of great importance is a search and rescue mission. When a person is missing, the first few hours are the most critical. Artificial agents can go faster than human rescuers (for example, in the form of drones) and they can go to places which have restricted access to people. In natural disasters, like hurricanes, millions of people are on a verge of death in their flooded houses, desperately waiting for a help to arrive. It is an impossible task to try to save all at once using only human resources. More people would survive if AI could easily recognize people's faces, distinguish a human or an animal in distress from other things around them, and successfully navigate through trails, neighborhoods, and homes. In addition, the help would be even more significant if artificial agents could autonomously communicate with each other giving information of where there is somebody who needs help and what kind of help does he need. The agents need to express their perceptions using some language they will understand. In other words, one of the important tasks in creation of an AI is giving it a possibility of knowledge transfer between parts of an AI, like an "eye" and an "arm", or between different agents.

People have questioned what makes their cognition so much better than computer's since middle of 20^{th} century. They thought that the structure of a brain plays an important role in how people learn and perceive the world. Billions of cells, called neurons, comprise a brain. They form connections to each other such that information in the form of electrical signals can travel from one neuron to another. We know that this system gives rise to a powerful mind, which can recognize objects, solve tricky puzzles, and learn about our world and the Universe. Thus we hope that if we create a system similar to an animal brain, then it might learn the same way and be as intelligent as humans. The attempt to create such a system was the development of neural networks.

Of cause, to function like humans, and have the full picture of the world around them, computers need all senses people have: vision, hearing, smell, taste and touch. These processes are complex and not easy to reproduce. The first step in this task is to give an agent a sense of vision and teach him to recognize and represent shapes, people, places, etc. The goal of this work is to extract abstract representations of real life objects, mapped into 2D shapes, based on both sensor (image) data and actuation (movement of an "eye") data. For the purpose of a knowledge transfer, we want to have a description of a shape in terms of a sequence of actions which generate the shape. This way, the description is not tied to a concrete actuation system, but gives general shape replication directions for any system. For this purpose the notion of wreath product is a good match, because it provides an abstract robot control scheme description which can be mapped to diverse actuation systems (either within the same robot or across distinct robot platforms). Such a representation is based on shape symmetries as defined by group actions on point sets. Shapes can then be classified according to the resulting wreath product. In particular, we propose a set of computationally exact recurrent neural networks (CERNNs) for wreath product discovery and measure their performance in terms of the robustness of the method on a variety of shape deformations. The computationally exact network in this case means that it doesn't learn, but has predetermined weights for discovering rotational, translational and point symmetry. This makes it more precise than a learning neural network, and it doesn't require large quantity of training examples. Thus we provide novel solutions for (1) providing a wreath product based symmetry analysis that combines perception and actuation information in the representation semantics of shape, and (2) realizing this computation in a set of computationally exact recurrent neural networks. Testing of these networks showed robustness in finding correct edge elements, as well as translational and rotational symmetries of different shapes. In the following sections, we first describe *DISCERNN*, our RNN representation and compilation framework; next, CERNNs are given for the efficient computation of symmetries, and lastly experimental results are described on a set of images and conclusions are given.