Teaching Robots Biologically Inspired Tasks

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Abstract

This paper will cover how I utilized a neural network to train a Jetbot to imitate predator-prey relationships. The Jetbot was created using blueprints provided by NIVDIA. The robot was trained using PyTorch and its various open-source libraries. The goal of this project was to improve upon the research conducted by William Grey Walter and Michael Arbib. Both conducted previous work on replicating animal behavior through predator-prey relationships to examine the interconnectedness of the brain. By replicating their research using a neural network, I can better emulate predator-prey relationships and closely analyze the connectivity of the brain.

Keywords: neural network, robotics, biology, machine learning

Introduction

Robotics has seen a dramatic evolution since its advent. Early robotics saw its place in a child's playroom as wind-up toys with preprogrammed motions (Nocks, 2017). Now robotics can be seen in hospitals assisting with complex surgeries (Bogue, 2011) or in disaster zones searching for survivors (Tadokoro, 2005). A major contributor to this evolution was the inspiration garnered from biological beings.

Scientists looked to the anatomy of living creatures to overcome challenges with robotic movement. Big Dog was developed by Boston Dynamics to overcome problems faced by wheeled robots (Raibert et al., 2008). Another example is micro aerial vehicles (MAVs). The downside to using these was its inability to land anywhere. Scientists looked to flying insects to solve this problem and developed a MAV that can perch and take off from any surface and consequently land safely (Granule et al., 2016).

Scientists also analyzed behaviors to understand and implement complex thinking. Two examples are William Grey Walter's tortoises (Walter, 1953) and Michael Arbib's Rana Computatrix (Arbib 2003). Walter and Arbib studied predator-prey relationships in various animals and replicated these behaviors using the technology available to them at the time. They believed that by studying these relationships they would gain insight into the association between brain and action (Arbib, 2003). Both will be discussed further in the background section of this paper as they are the direct inspiration for this project.

This project sought to improve on the previous work done by Walter and Arbib by utilizing a neural network. A neural network is a mathematical-based learning system that uses a network of functions to understand various kinds of data. The concept originated from human biology and how the human brain functions using neurons to interpret inputs from the biological senses (Schmidhuber, 2015). Our goal was to mimic predator-prey behaviors by training the neural network to identify predator versus prey and assigning actions to the different identifications. By doing this, we could observe how the brain interprets situations and executes actions.

Previous Research

There has been extensive research into predator-prey relationships with regard to robotics. Two of the most fundamental projects are William Grey Walter's tortoises and Michael Arbib's Rana Computatrix. Walter's tortoises were inspired by neuroscience and the complex interconnectedness of neurons within the brain (Walter, 1953). Arbib wanted to improve on Walter's work by making the thinking process more like the biological life form he based his robots on (Arbib, 2003). Both scientists were interested in exploring predator-prey behaviors as a means for understanding thinking.

William Grey Walter is considered a founding father of creating authentic artificial life (Holland, 1997). He achieved this honor through the creation of a series of tortoises designed to replicate complex behaviors by utilizing a rich interconnectedness between a minimal number of parts (Walter, 1953). Walter's first design was called the "Machina Speculatrix" which roughly translates to "machine that thinks" (Mataric, 2007). It was a simple design with the only resemblance of a tortoise being its clear plastic shell protecting the inner mechanical components.

There was one driving wheel controlled by a steering and driving motor. Attached to this wheel was a single photoelectric cell. This cell took in the light as sensory input and was attached to the driving wheel to ensure it was always pointing in the direction the robot was facing. The robot was taught to react to light in specific ways. If the light was of high intensity, it was programmed to flee. If the light was of low intensity, it was programmed to approach. This mimicked remedial predator-prey behavior exhibited in tortoises and other animals (Walter, 1953).

Michael Arbib believed that while Walter's tortoises were a pivotal invention in robotics evolution, they were not truly "thinking" machines. He sought to improve on Walter's research by creating his own set of robots exhibiting frog and toad-like visuomotor coordination. He began by making robots with basic predator-prey functions, like those of Walter's tortoises. A small object would represent a prey, while a large object would represent a predator. If a small moving object were presented, the robot would snap at the object. If a large moving object is in view, the robot would avoid the object. Arbib took this a step further by relating the behavior to the anatomy of a frog (Arbib, 2003).

Each eye of a frog sends visual information to the opposite side of the brain, and the midbrain region known as the tectum. Layered in front of the tectum is the pretectum. Arbib made the hypothesis that the small moving object identification and the resulting action are in the tectum while the large moving identification and corresponding action are in the pretectum. Through this additional programming, Arbib observed an interesting behavior. When two small moving objects were identified, the robot would snap in between the two objects rather than picking one over the other (Arbib, 2003). The same behavior can be observed in sentient frogs. This showed that Arbib was successfully able to mimic animal behavior in his Rana Computatrix and create a truly thinking machine (Murphy, 2019).

Methodology

Inspired by these two scientists, I sought to replicate predator-prey behavior to study the interconnectivity of the brain. To improve on their work, I utilized a neural network to better model a biological brain. I trained this neural network to identify a blue pool ball as a predator and a yellow pool ball as a prey. I then analyzed what this programmed behavior can teach us about biological behavior. The remainder of this paper will discuss the details of how this was accomplished.

There are several different ways to examine the interconnectivity of the brain. For this project, I focused on functional connectivity. Functional connectivity is based on statistics and refers to parts of the brain that are dependent on one another regardless of having direct structural links (Sporns, 2007). The living brain relies heavily on statistics to manage the flow of information gathered from the environment and determine behavioral output (Chen, 2019). Because of this, neural networks are designed to make decisions based on statistical inferences to model the brain as closely as possible.

For the design of the robot, I decided to use NVIDIA's Jetbot. NVIDIA provides all design files and a complete list of parts to create the Jetbot from scratch on GitHub. My mentor, Dr. Xuejun Liang, followed this guide to construct the Jetbot I used for this project. The Jetbot utilizes the computational power of the Jetson Nano. This computer allows users to run multiple neural networks in parallel (NVIDIA). I also decided to use the convolutional neural network (CNN) AlexNet.

AlexNet is different from earlier CNNs due to its hierarchical image classification structure. At the lower layers of the network, images are seen as highly pixelated with low resolution. This layer is used to determine rough features like the edges of an object or color. At the higher layers, images are processed in greater detail. By performing image classification in this manner, the computational time is greatly decreased allowing large datasets to be analyzed and the creation of accurate models to be produced (Krizhevsky et. al, 2012). Due to these advantages, AlexNet was an ideal CNN for the project.

I trained the robot to perform three actions, collision avoidance, avoidance of predators, and attraction to prey. The intention of teaching the robot collision avoidance was to simulate an animal moving about its territory while looking out for predators or prey. I used a table to simulate its territory and two pool balls to represent predator vs prey.

I first created categories that separated and labeled images taken from a mounted camera. These categories were: blocked, free, predator, and prey.

The categories blocked and free were specific to the collision avoidance function. These simply signified whether the robot was free to continue its path or if it should stop to avoid a collision. The categories predator and prey refer to when there is a predator or prey in the robot's field of view.

To train the model to recognize these categories, I took two hundred pictures using the mounted camera for each category. These pictures were stored in the Jetson nano in their corresponding directories. For the collision avoidance, I slowly moved the robot along the edge of a table taking a picture about every inch and labeling this "blocked". I then moved the robot around the table first horizontally, then vertically, and lastly diagonally across every movable inch. These were labeled "free". For the predator-prey responses, I took pictures with a blue pool ball in its vision and a yellow pool ball in its vision. The blue pool ball was used to represent a predator. The yellow was used to represent the prey. It was important to take these pictures at different times during the day as the table that was used was next to a window and the change of light affected the accuracy of the model. I then ran these images through a training program.

AlexNet divided the image set equally. Half of the set was used to train the model and the other half was used as a test set. While a higher number of epochs is favored, five epochs were used to find the best training model. This was due to the large number of images the training algorithm had to handle. With just the collision avoidance being trained (400 images), it was easy to have ten epochs. The time for compilation was too costly to maintain the ten epochs when the combined total for the predator and prey detection and the collision avoidance (1,000 images) were used. Therefore, the number of epochs was reduced to 5 to allow for retraining if necessary. The training program would calculate the accuracy of each epoch and pick the best one to assign as the model.

The final step was to program behaviors for each category. This was done using a series of if-else statements. For the collision avoidance, if the probability of the view being blocked was greater than 0.5 or 50%, the robot would first move back then to the left. Otherwise, it would continue forward. For the predator-prey identification, if the probability of a predator being in the view was greater than 0.5, then the robot would move backward. If the probability of prey being in view was greater than 0.5, then the robot would move forward.

Results

The robot was able to successfully execute collision avoidance. It was also able to differentiate between predator and prey. When presented with the blue ball, it moved away from it. Thus, showing it recognized it as a predator and avoided it appropriately. When presented with a yellow ball, it moved towards it. Proving that it identified it as a prey and responded correctly.

To test the robot's thinking, different colors of pool balls were used. A black, green, red, and orange ball was placed in view of the robot. When presented with the black or green balls, the robot responded as if there was a predator in sight. When presented with the red or orange balls, the robot would identify them as prey. If both the black and green ball were used, it would once again react as if it is seeing a predator. If both the red and orange ball were used, it would identify them as being prey and move towards them. If any of the combinations of a dark-colored ball and a light-colored ball was used, it would only identify the prey and move towards the object.

Conclusion

Using a neural network allowed us to closer examine functional connectivity due to its statistics-based approach. Like our brains, a neural network makes guesses as to what is identifying based on previous knowledge. This was exemplified when it was exposed to a color of a ball it had not seen before. For example, when exposed to the black ball, it responded as if it was exposed to a blue ball. This is due to the robot's limited knowledge base. The robot was only programmed to respond to a situation where a blue ball was in view or when a yellow ball was in view. Upon seeing the black ball, it had to make a statistical guess about what it was seeing and therefore thought it was more likely a blue ball in view rather than a yellow one. It then acted accordingly and moved away from the ball. By observing this behavior, it is clear that actions are dependent on statistical inferences made by the brain.

Future Research

In continuing this project, I would like to pick a specific animal and model its brain as closely as possible. By doing this, I could better analyze the brain processes the living creature would perform. Additionally, it would be interesting to add more features such as stalking the prey upon recognition. This way, I can examine how the brain performs different types of actions. For predator recognition, it would be interesting to add a defense mechanism that relates to the specific animal I would be attempting to model. By doing this, it would be easier to see what steps the brain needs to take and can be compared to the brain usage different defense mechanisms need. This project has a lot more potential, and it is something I suspect others will expand on in the future.

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