Vision based Indoor Obstacle Avoidance using a Deep Convolutional Neural Network

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Abstract: A robust obstacle avoidance control program was developed for a mobile robot in the context of tight, dynamic indoor environments. Deep Learning was applied in order to produce a refined classifier for decision making. The network was trained on low quality raw RGB images. A fine-tuning approach was taken in order to leverage pre-learned parameters from another network and to speed up learning time. The robot successfully learned to avoid obstacles as it drove autonomously in a tight classroom/laboratory setting.

1 INTRODUCTION

The field of Deep Learning consists of algorithms that learn using massive artificial neural network architectures. Most Deep Learning models are built with the intent of processing images. Some of these architectures are capable of outperforming humans in tasks like classifying objects, which simply means differentiating one object from other objects (dog vs. wolf, e.g.). In this paper, we present an application of Deep Learning to the concept of autonomous driving for a TurtleBot type robot within a tight classroom/laboratory setting based strictly on images. The robot was able to successfully and autonomously drive without hitting obstacles within the environment.

Krizhevsky, Sutskever, and Hinton (2012) put forth a foundational paper in regards to Deep Learning. They developed a neural network with 60 million parameters and 650,000 neurons. This network had 5 convolutional layers along with a few pooling layers and 3 fully connected layers including a final output layer of 1000 outputs. At the time, they achieved a top-5 classification (of the 1000 classes) error rate of only 15.3% compared to a much higher second-place error rate of 26.2%. This paper contributed to the discussion of the importance of depth in neural networks by noting that removal of a single hidden layer dropped the top-1 classification error rate by 2%.

Szegedy et al. (2014) entered the ILSVRC challenge with a 22 layer deep network nicknamed GoogLeNet – in part because most of the engineers and research scientists on the team worked for Google at the time. The team won the competition with 12 times fewer parameters than Krizhevsky's deep network and obtained an impressive 6.66% error rate for top-5 classification. Following the pattern of improvements, He, Zhang, Ren, and Sun (2015) of Microsoft Research used a 19 layer deep neural network for the task and obtained an accuracy of 4.94% for top-5 classification. This was a landmark accomplishment as it is purported to be the first to beat human level performance (5.1%) for the ImageNet dataset.

The most relevant dataset to our research is that of CIFAR10 from the Canadian Institute for Advanced Research (Krizhevsky, 2009b). Alex Krizhevsky outlined the use of this dataset when he developed it in 2009 for his Master's Thesis during his time at the University of Toronto (2009a). Prior to this, tiny images on the scale of 32 x 32 were not easily labeled for classification tasks in regards to algorithms like Deep Learning. The CIFAR10 dataset includes 10 different classes: airplane, automobile, bird, cat, deer, dog, frog, horse, ship, and truck. The classes are set up in a way to be mutually exclusive. For example, automobile and truck are completely different categories. Krizhevsky developed different deep neural network models in 2010 to run training with the dataset. At the time he obtained the highest

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accuracy using this dataset as his best model classified objects correctly with a success rate of 78.9% (Krizhevsky, 2010). Since then, Mishkin and Matas (2016) have obtained 94.16% accuracy on the CIFAR10 dataset. Whereas, Springenberg et al. (2015) have obtained 95.59% accuracy and the current best performance is by Graham (2014) with an accuracy of 96.53% using max pooling.

There has been strong interest in using the TurtleBot platform for obstacle detection and avoidance. Boucher (2012) used the Point Cloud Library and depth information along with plane detection algorithms to build methods of obstacle avoidance. High curvature edge detection was used to locate boundaries between the ground and objects that rest on the ground. Other researchers have considered the use of Deep Learning for the purpose of obstacle avoidance using the TurtleBot platform.

Tai, Li, and Liu (2016) used depth images as the only input into the deep network for training purposes. They discretized control commands with outputs such as: “go-straightforward”, “turning-half-right”, “turning-full-right”, etc. The depth image was from a Kinect camera with dimensions of 640 x 480. This image was downsampled to 160 x 120. Three stages of processing were done where the layering was ordered as such: convolution, activation, pooling. The first convolution layer used 32 convolution kernels, each of size 5 x 5. The final layer included a fully-connected layer with outputs for each discretized movement decision. In all trials, the robot never collided with obstacles, and the accuracy obtained after training in relation to the testing set was 80.2%. Their network was trained only on 1104 depth images. The environment used in this dataset seems fairly straightforward – meaning that the only “obstacles” seems to be walls or pillars. The environment was not dynamic. Tai and Liu (2016) produced another paper related to the previous paper. Instead of a real-world environment, this was tested in a simulated environment provided by the TurtleBot platform, called Gazebo. Different types of corridor environments were tested and learned. A reinforcement learning technique called Q-learning was paired with the power of Deep Learning. The robot, once again, used depth images and the training was done using Caffe. Other deep reinforcement learning research included real-world evaluation on a TurtleBot (Tai et al., 2017), using dueling deep double Q networks trained to learn obstacle avoidance (Xie et al., 2017), and using a fully connected NN to map to Q-values for obstacle avoidance (Wu et al., 2019).

Tai, Li, and Liu (2017) applied Deep Learning using several convolutional neural network layers to process depth images in order to learn obstacle avoidance for a TurtleBot in the real world. This is very similar to our work, except they used depth images, the obstacles were just a corridor, and they train from scratch instead of using transfer learning as we did.

Our research provides a distinctive approach in comparison to these works. Research like Boucher’s does not consider higher level learning, but instead builds upon advanced expert systems, which can detect differentials in the ground plane. By focusing on Deep Learning, our research allows a pattern based learning approach that is more general and one which does not need to be explicitly programmed. While Tai et al. used Deep Learning, their dataset was limited with just over 1100 images. We built our own dataset to have over 30,000 images, increasing the size of the effective dataset by about 28 times. The environment for our research is more complex than just the flat surfaces of walls and columns. As in Xie’s work, in our research the learning was done on a dataset that was based on raw monocular RGB images. This opens the door to further research with cameras that do not have depth. Moreover, the sizes of the images used in our research were dramatically smaller, which also opens up the door for faster training and a speed up in forward propagation. Lastly, similar to a few of these works, the results of our work were tested in the real world as opposed to a simulated environment.

2 DEEP LEARNING

Consider a standard feed-forward artificial neural network that is fully connected between each layer being used to process a 100 x 100 pixel image. With 3 color channels, we would have 100 x 100 x 3 or 30,000 inputs to our neural network. This is a large number of inputs for a standard neural network to process. Deep Learning directly addresses this limitation.

The *convolution* layer passes convolution windows over the image to produce new images that are smaller. The number of images produced can be specified by the programmer. Each new image will be accompanied by a convolution kernel signifying the weights. Instead of sending all input values from layer to layer, deep networks are designed to take regions or subsamples of inputs. For images this means that instead of sending all pixels in the entire image as inputs, different neurons will only take regions of the image as inputs – full connectivity is reduced to local connectivity. We take an image and extract local regions of depth 3 for the color channels along with their respective pixel values and input them into a neuron. Supposing that our local receptive fields are of size 5 x 5, this neuron takes in an input of dimensions 5 x 5 x 3 for that particular portion of the 3 color channel image. The local receptive fields can be seen as small windows that slide over our image, where the number of panes on the window is predefined. These panes help determine what features under the window we want to extract, and over time these features are better refined. The weighted windows are commonly called *kernels*. Depending on the type of kernel, different features of the image may be highlighted, such as blurring and sharpening. In this way, networks can develop identification of complex patterns in datasets just by applying kernel filters. Deep networks develop these kernels through training without being explicitly programmed to do so. The only supervision is from a loss function in the output layer denoting how close the network's prediction was to the actual value of the image. Through training, these kernels become more fine-grained to reduce the loss function's output.

Pooling is applied to each one of the convolution images. Deep networks are stacked in such a way as to include many different types of layers. A general strategy is to follow a convolution layer with a type of layer called a pooling layer. The convolution layer is responsible for learning the lower level features of an image, such as edges. The pooling layer seeks to detect a higher level understanding of the lower level features from the convolution layers. Pooling is also good for building invariance to local translations. This means that even if the input region is slightly translated, most of the pooled output values will not change. By employing max pooling (defined below), dominant features, or regions with the largest values, can be extracted and fed into later layers of the network. Along with this benefit, the image is also reduced dramatically because it is downsampled in one of three ways:

1) Max pooling – The maximum pixel value is chosen out of a rectangular region of pixels.
2) Min pooling – The minimum pixel value is chosen out of a rectangular region of pixels.
3) Average pooling – The average pixel value is chosen out of a rectangular region of pixels.

Reducing the size of the image dramatically cuts down on the amount of processing needed to train the higher level features of the network. In terms of processing, the idea is similar to convolution as we still pass a window over our image.

Convolution and pooling dominate the discussion about types of network layers. However, there are a few other types of layers that were used in this research.

The Rectified Linear Unit (RLU) layer (Krizhevsky et al., 2012) has recently grown in popularity. Many researchers consider this over using the sigmoid activation function. In fact, they were able to accelerate convergence in their training by a factor of 6 times in relation to the sigmoid activation function using this function. This is a fairly straightforward operation: the function takes a numerical input X and returns it if it is positive, otherwise it returns -1 * X. This effectively eliminates negative inputs and boosts computation time since complex computations such as exponentiation are not needed.

The Local Response Normalization layer (Krizhevsky et al., 2012) imitates biological lateral inhibition – excited neurons have the capability of subduing neighbor neurons. A neural "message" is amplified and focused by this differential in neuron excitement. These layers allow neuron's with large activation values to be much more influential than other neurons. Following the pattern of feature recognition in every layer, these layers allow significant features to "survive" deeper into the network.

The fully connected layer, which is like any regular multi-layered perceptron, is generally the final layer if it's used in a network. The outputs of the neurons in this layer are the actual outputs of the network. Connected to this layer is the loss layer where the network compares desired outputs to actual outputs, and the learning is initiated here in terms of gradient descent updates.

3 THE ROBOT

The robot used for this research (Figure 1) was the "Deep Learning Robot" from Autonomous. Its basic functionality is essentially equivalent to that of the TurtleBot platform. The robot includes an Asus Xtion Pro 3D Depth Camera, a microphone embedded in the camera, and a speaker. A Kobuki mobile base allows it to rotate and move in any direction on the ground plane. Most importantly, it is equipped with an Nvidia Tegra TK1, which allows us to carry out Deep Learning computations on a GPU instead of having to resort to extremely long wait times for training with a CPU. This is its main difference from a regular TurtleBot. While the Tegra TK1 is a powerful mobile processor, it only has 2GB of memory. This is problematic for training very deep networks because holding too many parameters in memory causes the robot to crash. While training, the robot is unstable because of this limited memory so running multiple programs at the same time is to be avoided.

The robot comes equipped with the Deep Learning frameworks of Google TensorFlow, Torch, Theano, and Caffe (we used Caffe), and CUDA and cuDNN are provided for implementing Deep Learning on GPUs and for speeding up that computation. This robot is virtually a computer in itself, and it allows us to treat it as such as it is very compatible with Ubuntu 14.04. The TurtleBot framework works hand in hand with the Robot Operating System (ROS), which is used to control the robot and to have access to all information coming from any of the robot's sensors. ROS is an "open-source, meta-operating system" which allows hardware abstraction, low-level control and message passing between different modules/processes.

Figure 1: Photograph of the Deep Learning Robot.

4 OBSTACLE AVOIDANCE

The problem scenario is that of training a deep neural network to learn autonomous driving of a vehicle in a tight, chaotic room/office environment. To test the functionality and success of the program, the performance of the robot was compared to the end goals. The end goals are primarily that the TurtleBot should autonomously follow an approximately rectangular path in a tight environment without colliding into obstacles. A description of this environment is provided below.

4.1 Environment

The Robotics Lab with obstacles in the room provides a reasonably complex environment for our tests. Figure 2 demonstrates this approximate environment set up. The approximate rectangular path that was configured was the perimeter of a long lab table. This table only has 3 planes of support on the underside; otherwise there are gaps underneath the table. White rectangles with dark borders are lab tables. The north and south sides of the tables are solid (2 of the planes of support), whereas the east and west sides have gaps. The gap size is large enough for the robot to be able to drive through, but chairs (white circles with dark borders) were placed in those locations. The total radii of the chairs are larger than the circles shown because the feet of the chairs extend out further. There is no gap for the robot to move in between neighbouring chairs (in most cases). The dark brown rectangle (southwest corner of the lab) is a colony space – boxed off area of the lab that may be used for other experiments, but there are borders (one foot high solid walls) that the robot would need to avoid hitting. The golden rectangles (north and south walls of the lab) denote cabinets which the robot must also avoid. The red rectangle in the middle of the figure shows the path around the center table that the robot must follow or the general path it needs to go in on its way as it avoids chairs, tables, boxes, etc. In separate runs this path must be completed in both clockwise and counter clockwise directions.

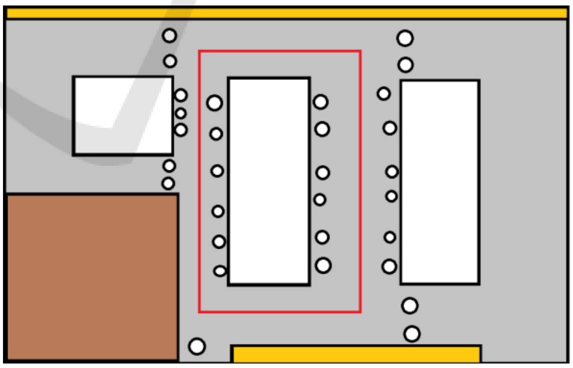


Figure 2: A visual of the environment with lab tables, chairs, and cabinets. Images are provided below to help understand this environment even more. The top of the drawing is approximately north.

One can see from Figure 3 that the gaps were closed with moveable round chairs. Each chair has 5 rounded legs and a circular stump. The chair heights can be adjusted and the orientation can change 360 degrees for both the base and the actual seating. Sample images are provided in the Figures 1, 3, and

4 to visualize different possible orientations for the chairs. These were chosen as the main objects of interest because they are not solid – there is clearly a good amount of gap area in between the legs. This allows for complexity in defining what an obstacle is and what and obstacle is not. The robot must not simply learn to follow the color of the carpet because even the gaps reveal the carpet.

Figure 3: Photograph showing chairs and spacing.

The camera for the robot faces down at about 40 degrees from the vertical position, so it is important to design an environment that is complex enough, in terms of objects close to the ground, to be a problem of interest. To highlight the point of this experiment, if the environment was built only using cardboard or other flat material as the main obstacle in the environment, then there would be a fairly straightforward solution. There would not be much variety, apart from lighting conditions, as to what material needed to be avoided. By using the chairs, the environment was more natural and complex. Not only were the chairs not solid surfaces, they were typically moved by students overnight. While they might be in the same relative location, the orientations were completely different each time. This adds complexity to the problem because it is not easy for a pattern to be developed since the orientation keeps changing. This means that for obstacle avoidance to be successful the deep neural network necessarily needs to develop an “understanding” that chairs are to be avoided. With enough gaps in between chairs and the legs of the chairs having significant gaps, the robot will still see the carpeted area. Thus, it cannot just develop a control program to follow a carpeted area, but instead needs a more complex pattern to be recognized from the dataset.

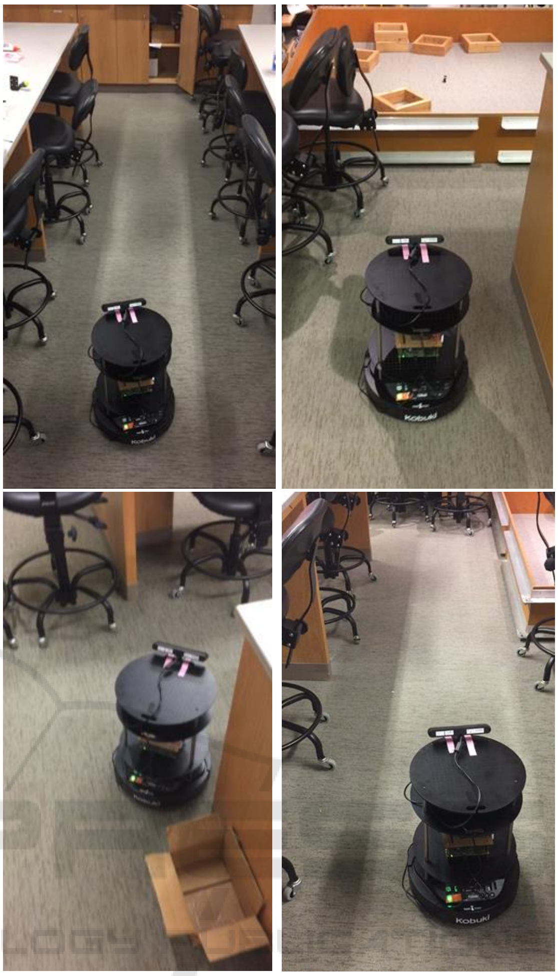


Figure 4: The images above demonstrate various obstacle avoidance scenarios.

It is important to establish guidelines as far as environmental set up because there may be scenarios that are impossible for the robot to solve. In our research, we dealt with two. In the first, if there is enough of a gap between two chairs the robot may make the decision to go straight instead of turning away from the chairs. In the second, if the robot is facing a cabinet directly head on. Even for a human with limited peripheral vision, it would be impossible to know which direction to turn. There is no way to have metaknowledge about which direction contains an obstacle and which does not. This is not a fair scenario to include in the dataset. To solve the former of the two issues, the environment included chairs that were placed close enough to have a small enough gap that the robot would not be able to fit through. To solve the latter of the two scenarios, cabineted areas included an open cabinet that swivelled to a direction the robot was supposed to avoid. Not only does this add more chaos to the environment (there are various different items in the cabinets which adds to the complexity of developing a pattern), but it also establishes rough guidelines as to the correct path.

Chairs, cabinets, and tables were not the only obstacles to avoid. A few images in the dataset included small cardboard boxes. A good amount of the dataset included the borders of a colony space environment. It was important to include obstacles like this in order to confirm that the concept of obstacle avoidance was being abstracted instead of the robot only avoiding black colored objects (the black chairs). It is also significant to note that students used the lab throughout the day and night, so conditions of the carpet changed while the dataset was being developed. For example, coins were found laid out on the ground near a turn in the path on one day. On another day, shreds of paper were at different locations on the path. We decided not to remove some of these items while building the dataset because it only adds to the diversity in what we might consider edge cases.

4.2 Dataset Collection

During data collection the robot was controlled remotely by a user on a keyboard (connected through a computer on Bluetooth) as it was driven around the lab following the path in both directions. The robot maintained continuous forward movement as the operator designated left, right, or straight. To increase the diversity of the dataset, different starting points were chosen and hard scenarios such as being close to walls were considered. Overall, 30,754 images were collected and labelled.

The script processed about 10 images per second, but not every image was saved. While no time record was kept, an estimated 1.5 – 2 hours were spent on trial runs and collections. In the initial testing conditions, we found that there were edge cases that were missing, so more data was added over time. By default, the images from the Asus Xtion Pro are of dimension 640 x 480. While this would provide a great amount of detail to train on, it would take an incredible amount of processing power and time to train to a significant accuracy. For our deep network we downsample this image to 64 x 64 (Figure 5).

5 DEVELOPMENT OF DEEP NEURAL NET ARCHITECTURE

We initially started by using an imitation of Alex Krizhevsky's deep network architecture to solve the CIFAR10 dataset. The plan was to augment this network with our own dataset. We obtained about 74% accuracy for that dataset. We took the weights of the network from it having learned the CIFAR10 data, and then fine-tuned it for our own purpose – obstacle avoidance while driving autonomously.

The thought for fine-tuning was inspired from the notion that the lower level features detected by the network are general enough to be applied to the problem of obstacle detection. Intuitively, there is a large difference between detecting an airplane and detecting a dog or a cat. However, Krizhevsky's network is capable of differentiating between the two based on the same kernel weights. That seems to be a large area of coverage for the type of data provided. The other thought here was that Krizhevsky's network was trained on 32 x 32 dimension images. Since our images will be 64 x 64 pixels, we may expect that there will be a boost in accuracy.

The complete network used for this research is shown in Figure 6. It is split into three lines to ease the visualization. We can see that there are 3

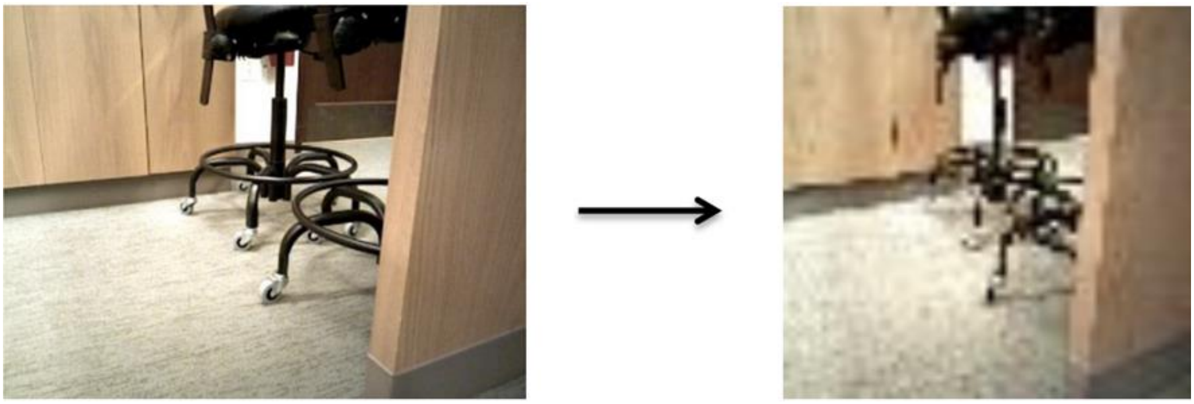


Figure 5: Reducing the image resolution from 640 x 480 to 64 x 64.

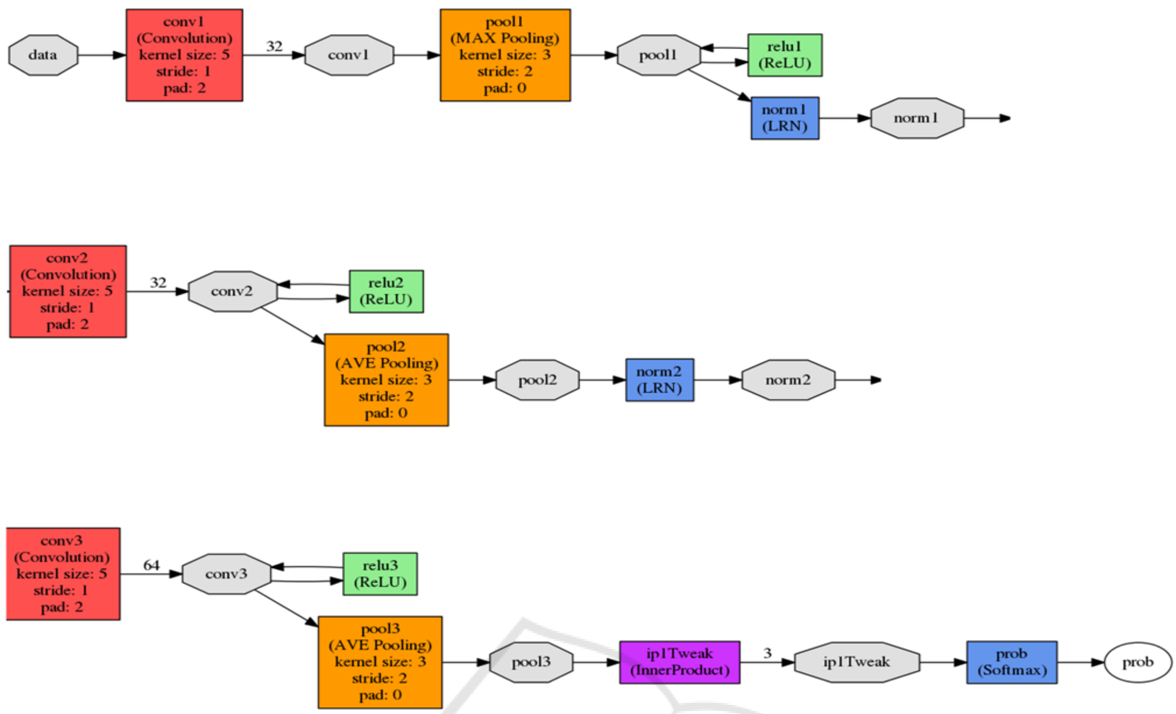


Figure 6: The final architecture for the deep network. This is inspired by the architecture for solving the CIFAR10 dataset. The rectangles represent layers. The octagons represent data.

iterations of the layer combinations of convolution, pooling, and normalization. Note that the fine-tuning of the network is evident from the visual. The layer "ip1Tweak" is labeled as such because the final layer of Krizhevsky's network was removed and replaced with an inner product ("ip"), or also considered fully connected, layer that only had 3 outputs. This is signified by the value 3 above the ip1Tweak layer in the visual. The 3 outputs correspond to the decision making of the TurtleBot in terms of autonomous driving directions. The original network included 32 convolution kernels for the first convolution, 32 convolution kernels for the second convolution, and 64 convolution kernels for the last one. We can also see how each convolution layer is immediately followed by a pooling layer. Every convolution layer also includes a rectified linear unit attached to it. Local Response Normalization also appears to be an effective addition to this network, as it augments the outputs of 2 of the 3 pooling layers. The dataset was split as such for the final network: 23,065 images for training and 7,689 images for testing – a 75% training split of the entire dataset.

The hyperparameters were:

- testing iterations: 100; basically how many forward passes the test will carry out.
- batch size: 77; this is for batch gradient descent – notice that batch size * testing iterations will cover the entire testing dataset.
- base learning rate: 0.001
- momentum: 0.9
- weight decay: 0.004
- learning rate policy: fixed
- maximum training iterations: 15,000
- testing interval: 150; testing will be carried out every 150 training iterations.

These hyperparameters were determined through several experiments in order to find the desired level of accuracy and performance. Some of these parameters are surely subjective. For example, we considered testing interval to be much less than it usually is for large networks (on the order of 1000). The reason for making this a small value is so that we can analyze shifts in learning in a decent amount of time instead of having to wait for over half an hour. The number of maximum iterations was chosen as an estimation of the number of epochs the network may have needed to stabilize. The batch size of the training data is 77 images, thus we would need about 300 iterations to cover the whole training dataset. Hence, the number for maximum iterations was established as 15,000 in order for the network to go through about 50 epochs.

6 RESULTS FOR AUTONOMOUS DRIVING

Starting with a Krizhevsky network trained on the CIFAR10 dataset and replacing the final layer with a tweaked fully connected layer, we ran the Deep Learning neural network on 30,000 images generated for the obstacle avoidance problem. The network was able to obtain an accuracy of about 92% after 15,000 iterations (Figure 7). It took the network about 200 iterations to get to the 84% accuracy mark and around 2000 iterations to achieve an accuracy of 90%. Ten different test runs in the actual environment were completed where the robot was reversed after a completion of a lap in order to complete the lap in the both directions. The robot did, although rarely, slightly graze against the leg of a chair or a cardboard box. However, this did not change the trajectory of the robot and it was still able to complete its course. For this reason, these rare occurrences were not considered as major events for hitting an obstacle.

One could argue that the turning angle for the robot is the only issue here since this is such a tight environment. Though the network made the right decision, the movement of the physical robot may have been slightly too much. This can be corrected with very small tweaks in the values of turning radii for the different decisions, however this does not reflect on or add to the discussion about the performance of the deep network in itself.

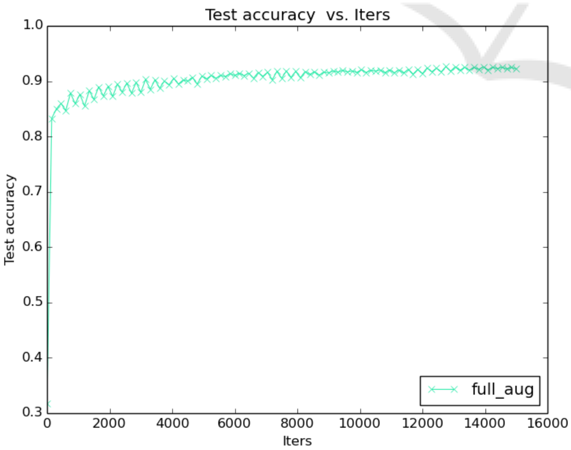
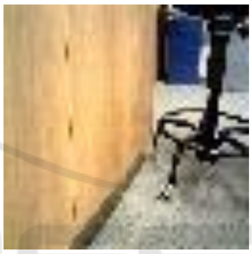


Figure 7: The performance of the network in relation to iterations for the fine-tuned Krizhevsky network trained with over 30,000 images. The first 15,000 iterations are shown. It took about 200 iterations to get to the 84% mark and by 15,000 it was at 92% accuracy.

6.1 Visual Analysis of Results

While observing the robot during particular situations of interest we noted that it routinely performed the correct action. The scenario of the open cabinet was not a challenge for the robot (Figure 1 and Figure 4 top left). As previously mentioned, this helped augment the robots path learning. We observed that the robot was successfully able to navigate the tight corridor and move away from chair obstacles (Figure 4 top images) and the border of the colony space, which showed that the robot learned to avoid more than just the chairs (Figure 4 right images). Although, the cardboard box was seldom included in the original training dataset, the robot clearly had pattern recognition broad enough to be able to avoid it (Figure 4 bottom left). Figure 8 shows three examples of the output of the neural network.



left 0, straight 0, right 1

left 0.73, straight 0.27, right 0

left 0.02, straight 0.96, right 0.02

Figure 8: A sampling of scenarios where the neural network made live decisions and the outputs of the NN are shown for each (they will total 1.0). The NN will have the robot turn right in the top scenario, left in the middle, and straight in the bottom.

7 CONCLUSIONS

The approach of fine-tuning Krizhevsky's network that solved the CIFAR10 dataset was highly successful. The robot effectively avoided obstacles in the original room where the dataset was collected. The robot also avoided colliding into other obstacles that were not part of the dataset – the deep network did not solely focus on chairs and cabinets as the only obstacles to avoid. In regard to accuracy, this approach seems more successful than the previous approaches that utilized depth. In the future, different dimensions (other than 64x64) may be considered. It would be valuable to potentially find a definable relationship between the image dimension and network accuracy.

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