Autonomous Trail Following using a Pre-trained Deep Neural Network

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Abstract: Trails are unstructured and typically lack standard markers that characterize roadways; nevertheless, trails can provide an effective set of pathways for off-road navigation. Here we approach the problem of trail following by identifying the deviation of the robot from the heading angle of the trail through the refinement of a pretrained Inception-V3 (Szegedy et al., 2016a) Convolutional Neural Network (CNN) trained on the ImageNet dataset (Deng et al., 2009). A differential system is developed that uses a pair of cameras each providing input to its own CNN directed to the left and the right that estimate the deviation of the robot with respect to the trail direction. The resulting networks have been successfully tested on over 1 km of different trail types (asphalt, concrete, dirt and gravel).

1 INTRODUCTION

A key requirement for off-road autonomous navigation is to be able to follow a certain path or trail in a natural and unstructured environment. The robot continuously follows a trail and at each instant takes a sensor snapshot of the trail "in front" of the robot. The goal is to take this snapshot and to estimate the deviation of the robot with respect to the direction of the trail and to then generate an appropriate motion command that moves the robot along the trail. The road fallowing version of the problem is aided by many detectable and well known features associated with highways and streets. This is to be compared to the somewhat unstructured nature of trails. The diversity of trail types presents many challenges for the task of fully autonomous navigation.

There are many possible approaches to trail following, however, this work utilizes an Inception-V3 (Szegedy et al., 2016b) CNN pretrained on the ImageNet dataset (Deng et al., 2009) to estimate trail deviation. Although the Inception-V3 CNN trained on ImageNet can be used to recognize trail heading, it has difficulty in distinguishing between deviations to the left and the right. In order to overcome this limitation here we propose a differential approach that uses two cameras, each using the same tuned CNN based on the Inception-V3 pre-trained network to address the trail following task.

2 PREVIOUS WORK

There is a large road following literature associated both with 'off-road' roads as well as hard surface roadway following. Space does not permit a full review of these approaches here, and the interested reader is directed to (DeSouza and Kak, 2002) and (Hillel et al., 2014) for surveys of the field.

There are many potential approaches to trail following. Here we concentrate on a CNN-based approach. The last ten years or so have seen a resurgence in NN-based approaches to this problem aided in part by substantive increases in computational power that enables 'deep' networks to be constructed and the vast amounts of labeled data that now exists to train these networks. NN-based approaches to road or trail following generally fall into one of two basic categories, systems that classify the state of the robot relative to the road and then use this information to steer the vehicle, and approaches that map sensor data to steering angle directly.

Road Surface Detection. This category of approaches first segments image pixels into *road* or *non-road* classes. This information is then used to estimate the best steering angle to keep the robot on the road while moving the robot forward. These approaches treat the problem as a classification problem (which pixels are road pixels) exploiting the wide range of classification approaches that are based on

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CNN's. For example, (Mohan, 2014), presents a deep deconvolutional network architecture that incorporates spatial information around each pixel in the labeling process. (Brust et al., 2015) and (Mendes et al., 2016) use small image patches from each frame in order to label the center pixel of each patch as either road or non-road. These patches are fed into a trained CNN to classify the label of the center pixel of that patch. These algorithms use spatial information associated with each pixel in order to label that pixel with high confidence. (Oliveira et al., 2016) present a method for road segmentation with the aim of reaching a better trade-off between accuracy and speed. They introduce a CNN with deep deconvolutional layers that improves the performance of the network. Another advantage of this method is that it uses the entire image as an input; not different patches of each frame and this helps to make the algorithm run faster and be more efficient.

Steering the Robot Directly. Work here can be traced back to the late 1980's and works such as ALVINN (Pomerleau, 1989). This approach uses a set of driver's actions captured on different roads such as one lane, multi-lane paved roads and also unpaved off-roads, to train the neural network architecture of the robot to return a suitable steering command to the robot. Work following this basic strategy continues today. To take but one recent example, NVIDIA (Bojarski et al., 2016) designed a system to train a CNN on camera frames with respect to the given steering angle of a human driver for each frame. An instrumented car is outfitted with a camera that simulates the human driver's view of the road, and a human drives the vehicle while the camera input and human steering commands are collected. A CNN is then constructed from this dataset using the human steering angle as ground truth.

CNN's have also been used to drive a robot on off-road trails and one such approach is presented in (Giusti et al., 2016). This work uses a machine learning approach for following a forest trail. Rather than directly mapping image to steering angle this approach categorizes the input image into one of 'straight', 'left' or 'right' and then uses the distribution of likelihoods over these three categories to compute both a steering angle as well as an appropriate vehicle speed. In order to collect training data three cameras are mounted on the hip of a hiker, one pointing 'forward' and one yawed to the right and the other one yawed to the left. Data is collected while the 'forward' camera is aligned with the trail. These three cameras are set up with a 30 degrees yaw from each other on the head of a hiker to record the dataset.

Table 1: TrailNet dataset training hyperparameters.

Training hyperparameters	Value
epochs	5
learning rate	0.02
train batch size	100
validation batch size	100
random brightness	$\pm 15\%$
# images per label for training	5000
# images per label for validation	625
# images per label for testing	625

Their dataset consists of 8 hours of video in forest-like trails and images are captured in a way that the hiker always looks towards the direction of the trail. Therefore, in a classification task, the central camera is labeled as "go straight", the left camera is labeled as "turn right" and the right camera is labeled as "turn left". These labels are then used to train a CNN in order to perform the classification task and outputs a probability of each class as a softmax function. They used a 9 layer neural network in order to do the classification task. These layers consist of 4 back to back convolutional and max-pooling layers followed by a 2,000 neuron fully connected layer and finally a classification layer (output layer) with three neurons which returns the probability of occurrence of each label. This DNN is based on the architecture used in (Ciregan et al., 2012). For evaluation purposes, the accuracy of this classifier is calculated based on the maximum probability of softmax function in the output of DNN. The reported accuracy is 85.2% for the classification task between three labels of "go straight", "turn right" and "turn left".

3 TrailNet DATASET

Key to a CNN-based approach is an appropriate dataset to train the network. For this work we collected the TrailNet dataset of different trails under various trail and imaging conditions (its capture is inspired by the approach presented in (Giusti et al., 2016)). TrailNet[1] consists of images captured from wide field of view cameras of different trail types, where each class of images has a certain deviation angle from the heading direction of the trail. In order to study the effect of surface type of the trails, each of the TrailNet dataset are further divided by trail types: (1) asphalt, (2) concrete (3) dirt and (4) gravel. TrailNet was captured with three omnidirectional cameras.

[1]TrailNet is available for public use at http://vgr.lab.yorku.ca/tools/trailnet

Table 2: Detailed test accuracy results of the straight/not-straight method with the three narrow camera geometry setup on all trail types. The 0° and overall columns show recognition rate for the two classes. Performance is also broken down for each of the $-60°$ and $+60°$ categories separately.

	Test accuracy			Subcategories accuracy		
Training dataset	**Overall**	**Not-straight**	**Straight**	$+60°$	$-60°$	$0°$
Asphalt	99.90%	99.95%	99.90%	100.0%	99.90%	99.90%
Concrete	99.75%	100%	99.20%	100.0%	100.0%	99.20%
Dirt	97.77%	100%	99.20%	100.0%	100.0%	99.30%
Gravel	99.13%	99.88%	98.14%	100.0%	99.24%	98.14%

Each of the cameras is a Kodak Pixpro SP360 (kodak, 2016), which provides a fish eye camera with a 214° degree of vertical field of view at 30 frames per second with a resolution of 1072×1072 pixels. A Pioneer 3-AT robot (p3at, 2017) was used as a mobile base in this work. During training the three cameras were mounted on a detachable circular mount on top of the robot, while during trail following only the two cameras directed to the left and right were used.

4 FINE TUNING A PRETRAINED CNN MODEL

Transferring knowledge from a trained network on a given task to another network operating on a target task is called transfer learning and a survey of different approaches in this domain is presented in (Pan and Yang, 2010). The basic approach involves taking a pre-learned CNN and then surrounding this CNN with a small number of layers and then training just these layers on the specific problem. In this approach the last layer of the network (also known as classification layer) which is a fully connected layer, is replaced with two new fully connected layers and only the parameters of these two layers are trained on the new dataset. This fine tuning approach transfers the mid-range features learned by the source network and exploits them in a new classification task. Obtaining a rich and vast annotated dataset on a new task is a very tedious and sometimes very expensive procedure. As a consequence, the fine tuning approach can be very helpful when the target task does not have a huge dataset from which to train a CNN from scratch.

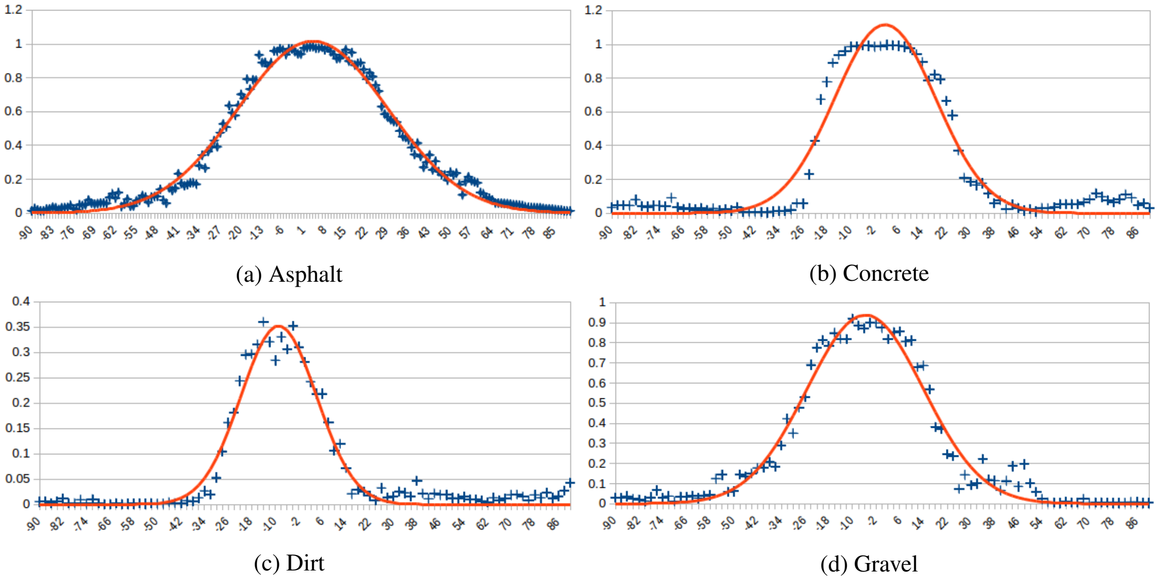
Here we explore using the pre-trained Inception network to differentiate between straight ahead trails and trails that are bending away from the straight ahead direction. In this method, labels are either straight (i.e., 0°) or not straight (i.e., $-60°$ or $+60°$). Hyperparameters used in the following training steps were common over the different training regimes followed and are provided in Table 1. Table 2 shows the performance on each trail type by their corresponding trained network.

In order to study the effect of the trail type in the task of deviation angle recognition on trails, the performance of each road-type (asphalt, concrete, dirt, gravel) network was tested on a test set from each of the trail types. Table 3 shows the performance confusion matrix. The "correct" recognizer works well on the "correct" trail type (the diagonal in Table 3) while the "wrong" recognizer shows reasonably good accuracy on the "wrong" trail type with some exceptions. The dirt network shows a reasonably good performance on all the other trail types, the asphalt network is reliable for asphalt and concrete, the concrete network shows a good performance only on concrete, and the gravel network also has a good ability to recognize the correct labels for the concrete dataset and the gravel dataset itself. But for best performance, a properly tuned trail-specific CNN performs best.

The ability of the fine tuned Inception-V3 CNN's to differentiate between straight ahead and not-straight ahead classes can be used to develop a differential strategy for trail following. Figure 1 shows the 0° classifier output results for each of the classifiers as the roadway curves from $-90°$ to $+90°$. For each response curve a normalized Gaussian is fit. The nature of the fits suggest that the networks have a symmetrical sensitivity for the positive and negative deviation angles from the trail. The Gaussian-like response fit also suggests that a classical difference of offset Gaussian (DOOG)(Young et al., 2001)-like approach could be exploited to combine multiple CNN response curves to estimate the direction of the trail relative to the robot.

Table 3: Confusion matrix for the straight versus not-straight trained networks on the test sets from their corresponding trails and other trail types. Poorly performing network-trail type combinations are highlighted in bold.

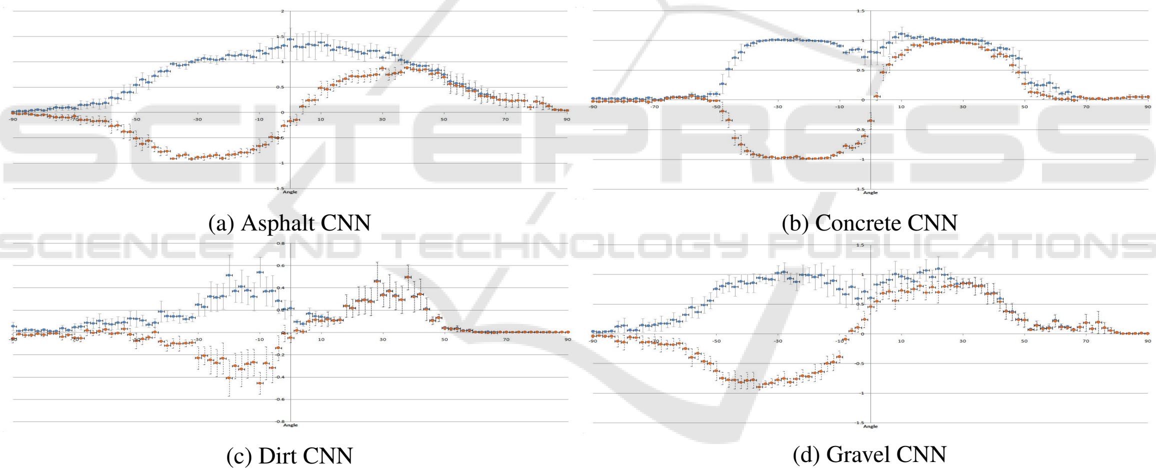
	Trail type (%)			
NN	asphalt	concrete	dirt	gravel
asphalt	99.90	96.69	**63.78**	87.26
concrete	85.34	99.75	**66.60**	**70.10**
dirt	92.40	93.95	97.77	95.15
gravel	84.72	98.83	84.33	99.13



(a) Asphalt (b) Concrete

(c) Dirt (d) Gravel

Figure 1: Blue points in the charts depict the 0° label output results of the trained networks on images between $-90°$ and $+90°$ on their corresponding trail type. Orange lines show a normalized Gaussian function fitted to the plotted results. The Gaussian fit is normalized to the maximum of the response curve. Note the different vertical axes for the various plots.



(a) Asphalt CNN (b) Concrete CNN

(c) Dirt CNN (d) Gravel CNN

Figure 2: Experimental values of G_+ (blue) and G_- (orange) with standard errors for generic camera geometry but different CNN terrain types. The horizontal axis of all charts is the angle of the heading of the robot γ with respect to the trail direction.

4.1 Differential Method

Rather than utilizing a single "forward facing" sensor here we utilize two such sensors each providing input to their own identical CNN and then utilizes the difference between two "straight ahead" classifier outputs obtained from cameras offset in orientation to the left and right to encode the trail direction. In order to find the optimal offset angle between the cameras the sensitivity functions of the CNN's with respect to the deviation angle of the robot γ relative to the trail is estimated (see Table 4).

Assume that the sensitivity function of the right and left CNN's are well described by the Gaussian distributions are G_1 and G_2, where G_1 and G_2 have the same standard deviation σ and means of $\mu_1 = \theta/2$ and $\mu_2 = -\theta/2$, respectively. The combined sensitivity function of the two CNN's is computed as the addition of G_1 and G_2 as $G_+ = G_1 + G_2$. The difference between G_1 and G_2 is denoted as $G_- = G_1 - G_2$. In order to have a stable overall sensitivity function G_+ and preventing G_+ from having a ripple in the center, θ should be chosen in a way that at $\gamma = 0$, $G_1 = G_2 \geq 0.5$.

Table 4 shows the characteristics of the Gaussian distributions of all of the networks on their corre-

(a) Asphalt map

(b) Concrete map

(c) Dirt map

(d) Gravel map

Figure 3: Overhead views of the test environments.

Table 4: Gaussian model parameters for each network.

NN	Asphalt	Concrete	Dirt	Gravel	Average
μ	3.96	1.47	-8.86	-5.68	-2.27
σ	24.85	16.99	12.85	19.69	18.59

sponding trail type and their averages across the different trail types. The average standard deviation $\sigma_{\mathbf{avr}} = 18.59$ was used to establish a generic camera separation. Figure 2 shows the performance of the differential CNN's on the different trail types. G_{-} encodes the deviation of the robot from the straight ahead direction while G_{+} encodes the confidence of this output.

From Trail Orientation to Steering Angle. There are a number of practical issues involved in computing a steering command from the estimated trail orientation. First, if the detector cannot detect a road, then some default steering angle should be chosen or in a full application this information should also be sent to higher level control. Second, there is a desire to not oversteer (an overshoot) the vehicle motion, and finally, if the steering angle is only changing by a very small amount the robot should not introduce small zero-mean fluctuations into the steering angle (the controller should have a deadband region). Properly addressing all of these issues is beyond the scope

(a) Asphalt (b) Concrete

(c) Dirt (d) Gravel

Figure 4: Snapshots taken along the trails.

of this paper, so here we adopt a very simple strategy for obtaining a steering angle change from the (G+, G-) pair. If $|G_{-}| < th_{-}$, then we assume that the robot is in a deadband region, and set the change in steering angle to be zero. If $|G+| < th_{+}$, then the detector does not detect a trail, and again we set the change in steering angle to be zero. For other angles we clamp the output change in steering angle to ± 0.1 rad/s. In all of the operating states of the robot, for the experiments described in the following section, the robot has a constant forward velocity of $20cm/s$.

5 EXPERIMENTAL RESULTS

In order to test the performance of the algorithm for the task of autonomous driving on trails, field trials were conducted on a range of trail types. Due to the battery capacities of the robot and the hardware used in this experiments, tests were broken down into 10 distances of 20 meters long. The following evaluations were used based on criteria typically used for autonomous driving systems (see (Bojarski et al., 2016));

- The maximum distance traveled over the the 20

Table 5: Autonomous field trial results for different trail types on 200 meters of paths shown in Figure 3 (a)-(d). The average values are computed based on the performance of the algorithm over ten different 20 meters pieces of path. Performance of the algorithm on asphalt and concrete paths was quit good, but deteriorated on dirt and gravel trails.

Parameters	Asphalt	Concrete	Dirt	Gravel
Maximum distance travelled (m)	20	20	19	20
Minimum distance travelled (m)	20	12	8	5
Average autonomous distance travelled (m)	20	18.6	15.6	13.1
Average number of human operator interruptions	0	0.2	1.2	1.4

meter test ranges before human intervention was required.

- The minimum autonomous distance traveled over each of the ten 20 meter test ranges before human intervention was required.
- The average autonomous distance traveled over each of the ten 20 meter test ranges before human intervention was required.
- The average number of human operator interruptions required in order to drive the vehicle 20 meters.

Figure 3 shows the paths chosen for the test on a map and Figure 4 provides a film strip of the robot in operation on all trail types. A chart of the results of the test on four different trails is shown in Table 5. Figure 5 plots a summary of these results.

The tests showed a number of interesting aspects of the algorithm. First, the algorithm performed very well on asphalt and concrete paths with the robot operating perfectly on asphalt and performing on average over 18m (in a 20m trial) without failure on concrete trails. Performance on dirt and gravel trails was less successful, but still showed quite good performance. It is interesting to note that the dirt trail was much narrower than the other trails tested (see Figure 5) but that even here performance was quite good. Worst performance was found on the gravel trail. One possibility here is that the control algorithm developed for gravel trails might need to be more tightly tuned for the gravel as the robot's tires exhibited poor performance on this surface.

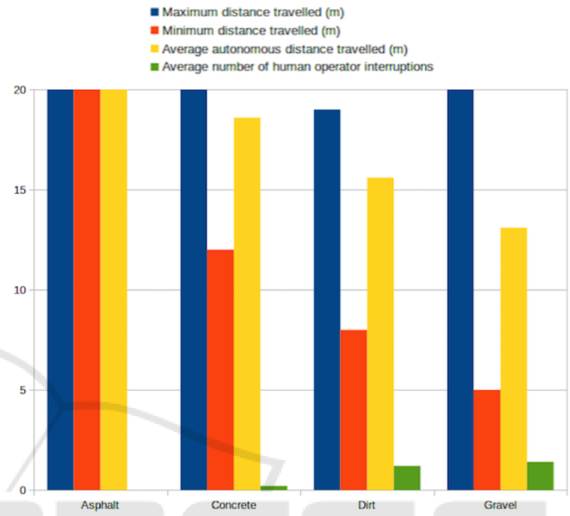


Figure 5: Autonomous test results plot on different trail types (see Table 5 for details). Vertical axis is in meters for distance traveled and count for average number of human operator interruptions.

6 CONCLUSION

This paper presented a refinement learning-based approach with the use of Inception-V3 network for off-road autonomous trail following. Experiments evaluated the nature, geometry and number of cameras that might be applied to the problem. Using a DOOG model a trail following algorithm was successful in navigating different trail types using a common camera geometry and using tuned CNN's for different trail types. End-to-end testing of the algorithm showed very good performance on asphalt and concrete paths, with poorer performance on dirt and gravel. Performance on dirt was still quite impressive given the narrow nature of such paths.

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REFERENCES

Bojarski, M., Del Testa, D., Dworakowski, D., Firner, B., Flepp, B., Goyal, P., Jackel, L. D., Monfort, M., Muller, U., Zhang, J., Zhang, X., Zhao, J., and Zieba, K. (2016). End to end learning for self-driving cars. arXiv:1604.07316.

Brust, C.-A., Sickert, S., Simon, M., Rodner, E., and Denzler, J. (2015). Convolutional patch networks with spatial prior for road detection and urban scene understanding. *arXiv preprint arXiv:1502.06344*.

Ciregan, D., Meier, U., and Schmidhuber, J. (2012). Multi-column deep neural networks for image classification. In *Proc. IEEE CVPR*, pages 3642–3649, Providence, RI.

Deng, J., Dong, W., Socher, R., Li, L.-J., Li, K., and Fei-Fei, L. (2009). Imagenet: A large-scale hierarchical image database. In *Proceedings of the IEEE International Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 248–255, Miami, FL.

DeSouza, G. N. and Kak, A. C. (2002). Vision for mobile robot navigation: A survey. *IEEE PAMI*, 24(2):237–267.

Giusti, A., Guzzi, J., Cireşan, D. C., He, F.-L., Rodríguez, J. P., Fontana, F., Faessler, M., Forster, C., Schmidhuber, J., Di Caro, G., et al. (2016). A machine learning approach to visual perception of forest trails for mobile robots. *IEEE Robotics and Automation Letters*, 1(2):661–667.

Hillel, A. B., Lerner, R., Levi, D., and Raz, G. (2014). Recent progress in road and lane detection: a survey. *Machine Vision and Applications*, 25(3):727–745.

kodak (2016). The Kodak camera website.

Mendes, C. C. T., Frémont, V., and Wolf, D. F. (2016). Exploiting fully convolutional neural networks for fast road detection. In *Proc.IEEE ICRA*, pages 3174–3179, Stockholm, Sweden.

Mohan, R. (2014). Deep deconvolutional networks for scene parsing. *arXiv preprint arXiv:1411.4101*.

Oliveira, G. L., Burgard, W., and Brox, T. (2016). Efficient deep models for monocular road segmentation. In *Proc. IEEE IROS*, pages 4885–4891, Daejeon, South Korea.

p3at (2017). The Pioneer 3-at robot website.

Pan, S. J. and Yang, Q. (2010). A survey on transfer learning. *IEEE Transactions on Knowledge and Data Engineering*, 22(10):1345–1359.

Pomerleau, D. A. (1989). ALVINN, an autonomous land vehicle in a neural network. Technical report, Carnegie Mellon University, Computer Science Department, Pittsburgh, PA.

Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J., and Wojna, Z. (2016a). Rethinking the inception architecture for computer vision. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 2818–2826, Las Vegas, NV.

Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J., and Wojna, Z. (2016b). Rethinking the inception architecture for computer vision. In *Proc. IEEE CVPR*, pages 2818–2826.

Young, R. A., Lesperance, R. M., and Meyer, W. W. (2001). The gaussian derivative model for spatial-temporal vision: I. cortical model. *Spatial Vision*, 14(3):261–319.