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Tsz Hong (Andy) Lau
University of Minnesota, Morris

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Tsz Hong (Andy) Lau
Division of Science and Mathematics
University of Minnesota, Morris
Morris, Minnesota, USA 56267
lauxx265@morris.umn.edu

ABSTRACT

Autonomous driving is the next biggest technological advance in the automobile industry. However, the current technology is still very much in its infancy. Networks of sensors such as cameras and LIDAR systems are used to record and measure the road condition. While neural networks are used to understand the road condition and make the correct decision to drive the vehicle. In this paper, we are specifically focusing on the road segmentation of autonomous vehicle technology. We will be going over the two approaches to road segmentation by Oliveira, et al [5] and Caltagirone, et al [2], and we will compare the performance of each approach on a road benchmark dataset called KITTI dataset.

Keywords

Autonomous vehicle, LIDAR, fully-convolutional network

1. INTRODUCTION

Every year, thousands of lives are lost to road accidents alone in the US. A lot of these accidents can be traced back to human errors. Car drivers of today are getting easily distracted on their cell phones and some are driving under the influence of alcohol and drugs. To address this, the automotive industry has been researching autonomous driving to eliminate the human factor in driving, thus allowing for safer roads for drivers and pedestrians alike. Autonomous drivers have the potential to be the perfect driver since they would not be distracted by their cell phones nor would they be able to drive under the influence. In addition, autonomous driving promotes better fuel economy and alleviates congestion by coordinating their routes. Autonomous driving requires an important component called *neural network* that has the ability to learn to drive. We will be specifically focusing on the road segmentation aspect of autonomous driving.

We will be looking at the two approaches of road segmentation by Oliveira, et al [5] and Caltagirone, et al [2]. Section 2 will give all relevant background information regarding how autonomous vehicles perceive the outside world and how neural networks work. Section 3 will explore the two approaches in greater detail and present a dataset designed to benchmark neural networks on road segmentation tasks. Section 4 will present the results gathered from the two approaches and how each of them performed compared to the other. Finally section 5 will give a summary of the paper and present current updates regarding the performance of road segmentation.

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2. BACKGROUND

In this section, we introduce the important concepts of autonomous vehicles. Autonomous vehicles perceive the outside world by having a network of sensors or cameras that are placed either around the outer perimeter or on top of the vehicle. There are currently two main sensors that autonomous vehicles use to understand the condition of the road: camera and LIDAR, which stands for Light Detection and Ranging. The network of these sensors send the gathered information such as images or point cloud information to an on-board computer which then analyzes the information to categorize or identify objects on the road. We will examine only a small, yet important area of autonomous driving, road segmentation, which is the task of classifying each pixel of an input into two categories: road and non-road. We achieve this goal with the help of neural networks and specifically a type of neural network optimized for pixel-based classification.

2.1 Camera and LIDAR

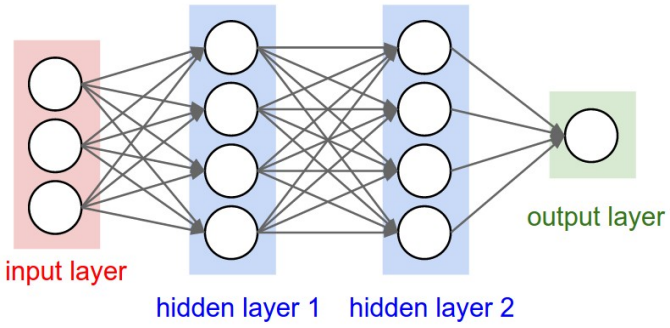
One of the ways autonomous vehicles gather information about the road is through a network of cameras mounted around the perimeter of the vehicle. These cameras take video recordings of the road which are then analyzed frame by frame. Cameras are limited in their data gathering capabilities. Adverse weather condition such as heavy fog impairs the vision of the cameras. Meanwhile, shadows are easily interpreted as objects. The computer in turn will have to take into account these factors in their analysis of the road condition as they will negatively impact performance and efficiency. [6]

LIDAR sensors have been used in conjunction with cameras in adaptive cruise control systems that are currently available in vehicles [6]. LIDAR systems have three major components: a transmitter, a receiver and an optical analyzer. The transmitter of a LIDAR system emits a pulsating laser beam that bounces back when the beam hits an object. The receiver then detects the said laser beam and the optical analyzer determines the time it took for the beam to return. Using this information allows the computer to determine how far the object is relative to the vehicle. [3] LIDAR sensors are usually mounted on top of a vehicle that is spinning 360°, collecting information around the vehicle.

2.2 Neural Networks and Deep Learning

In road segmentation tasks, the computer needs to discern road surfaces and non-road surfaces in the optical information sent from the network of sensors. Autonomous vehicles achieve this task through the use of neural networks. Neural networks are loosely modeled after human brain but on a smaller scale [1]. Natural human brains have a network of neurons, connected to each other by structures known as synapses. Neurons communicate through pulses which are sent from one neuron to the other. Neural networks work very similarly, nodes are neurons and are each connected by edges, each with a weight that indicates how much influence a value in one node has on another. Nodes are structured as a stack that forms a layer in a neural network. Models of neural network usually have multiple layers. All models would have an input and output layer but may have a different amount of layers in-between called hidden layers. Hidden layers can be seen as distillation layers, each layer distilling a specific feature from the input. Figure 1 shows a typical architecture of a neural network, it consists of an input layer, two hidden layers, and an output layer. Nodes between two adjacent layers are *fully-connected*, which means that each node in any given layer are connected to every node in adjacent layers.

Figure 1: A simple diagram of a neural network with two hidden layers [1]



A node typically takes in inputs from the previous layer, and applies a modifier called weight that either amplifies or dampens the input. These weights are what make a neural network powerful because it provides a way for us to train a network. We discuss this concept later in section 2.4. The nodes sum up all the weighted inputs from the previous layer, and then pass the summation result to an activation function that returns a single value. Without a non-linear activation function, neural networks can only express linear relationships between input and output. By introducing some non-linearity into a network, the model can predict more complex functions, thus increasing the capability of a network. The output of the activation function is then compared to the threshold value: if the output exceeded the threshold value, the node will send the output to the next layer of nodes. This process will continue until it reaches an output layer, which usually outputs a vector of class scores for a list of predicted events. As an example, a neural network tasked to recognize a hand-written digit will output a vector of class scores for each digit. This entire operation is called *forward propagation*.

Neural networks have had many real-world applications, from character and speech recognition to a prediction of a particular event. In the topic of road segmentation, a road scene image is fed into the neural network and each pixel of the image is classified as either road surface or non-road surface. As we discuss in section 2.3.1, a regular neural network is not optimized for this sort of operation. In fact, a type of neural network called *fully-convolutional network* is more optimized and more suitable for road segmentation. As discussed before, a regular neural network only computes a vector of class scores. In the interest of road segmentation, we are aiming to reproduce the same exact image as the input with the same resolution but with road and non-road surfaces labeled. But before we delve into fully-convolutional network, we need to understand its predecessor convolutional neural network (CNN). CNNs are mainly used for image classification in which an object of an image is classified into one of several fixed and pre-determined categories.

2.3 Convolutional Neural Network

Convolutional Neural Networks (CNN) are designed to process data that come in the form of images. A color image is transformed into three 2-dimensional arrays each containing one of the three color channels in the image. CNN is optimized for image classification compared to regular neural network because of its inclusion of two new types of layers: convolutional layers and pooling layers.

2.3.1 Convolution Layer

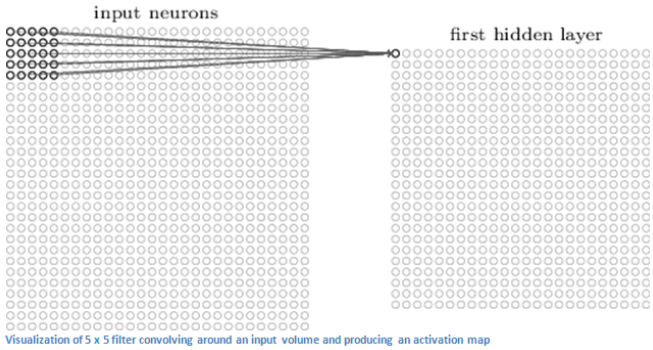
The convolution layer is the core building block of a convolutional neural network. The convolution layer consists of layers of filters with each of layer looking at a specific feature of the image. For example, one filter might be looking for edges while another is looking for curves. A filter is only looking at a small spatial area of the original input but would convolve across the width and height of the input image. The size of this small area is a parameter we can control (hyper-parameter) called the receptive field. This aspect of convolution layers is what makes CNN more optimized for image classification. A filter is made up of an array of trainable weights, and these weights are the same no matter where in the image the filter is applied as the filter is convolving around the image. In regular neural networks, a node inside the first hidden layer would have weight corresponding to all the elements inside the three 2-dimension arrays. For image classification problem, this fully-connected aspect of a regular neural network does not scale well to images [1]. The amount of weights needed to be trained would increase exponentially as the image size increases. The design of convolution layers allows for less weights to be trained (only those needed by the relatively small receptive field of the filter) which decreases training time and computational load.

In the forward pass, starting from the top left corner, the filter inside the convolution layer will slide across the width and height of the input volume and multiply the weight in the filter with the pixel value of the input image. The multiplications are then summed up and stored in the same relative position of what is called a feature or activation map as seen in Figure 2. Since the convolution layers have layers of filters, each layer results in a feature map that is then passed onto the subsequent layer for further analysis.

Another aspect we need to consider is the hyper-parameters

that control the size of the output feature maps: the depth, stride and zero-padding. First, depth of the output volume corresponds to the number of filters we would like to use, each learning to look for something different in the input, i.e. curves or edges. Second, the stride correspond to how many pixels we move the filter at a time, if the stride is 2, then the filters jump 2 pixels at a time when we slide them around. Third, zero-padding is a hyper-parameter responsible for padding the input volume with zeros around the border. There are some cases that one would need to pad zeros around the border in order for the receptive field considered and the stride to consistently cover the entire image. [1][8]

Figure 2: Visualization of 5x5 filter convolving around an input volume and producing an activation map [1]



2.3.2 Activation Layer

It is common to include an activation layer right after the convolution layer. An activation layer is simply a layer with activation functions. As mentioned before, activation function is used to introduce some form of non-linearity into the network. The most common activation function is the ReLU, stands for Rectified Linear Unit. ReLU has the following form, $f(x) = max(0, x)$. It is the most common activation function because of its low computational cost compared to other activation functions [1].

2.3.3 Pooling Layer

Pooling (down-sampling) layers are usually inserted in between successive convolution layers. The purpose of these pooling layers is to reduce the spatial size of the feature maps from the convolution layers thus, reducing the amount of parameters and computation in the network. Two hyper-parameters need to be considered for pooling layers: spatial extent and stride. Spatial extent represents the width and the height of the input layer to be considered. The most common down-sampling operation is max, giving rise to max pooling. To give an example, a spatial extent of 2 and stride 2 means each max takes in 4 numbers (2 x 2 square) and finds the max of those numbers. The result of the pooling layer are these condensed feature maps that are then passed on to subsequent convolution and pooling layers.

2.3.4 Fully Connected Layer and Softmax Layer

The fully connected layer is sometimes the final layer in a CNN. Like the name suggests, this layer is fully connected to all the feature maps compiled from previous convolution and pooling layers. This layer is responsible for the classification of the object in the image. By taking in inputs from all previous layers, it collects the global context information instead of the local information collected in the convolution layers. This layer computes an N dimensional vector where N is the number of classes. Each number in this vector represents the probability of a certain category.

Some CNN include a softmax layer at the very end of the network to scale the class scores into a range from 0 to 1, effectively changing the vector of class scores into a vector of probability for each class. In addition, softmax layer acts to amplify the differences between the probability for each class. In road segmentation, each pixel would have a vector of two probabilities each representing the probability of the pixel being the road or non-road surface. Finally, we would hope to see that the difference between the road and non-road probabilities is large so that no ambiguity is present in the network prediction.

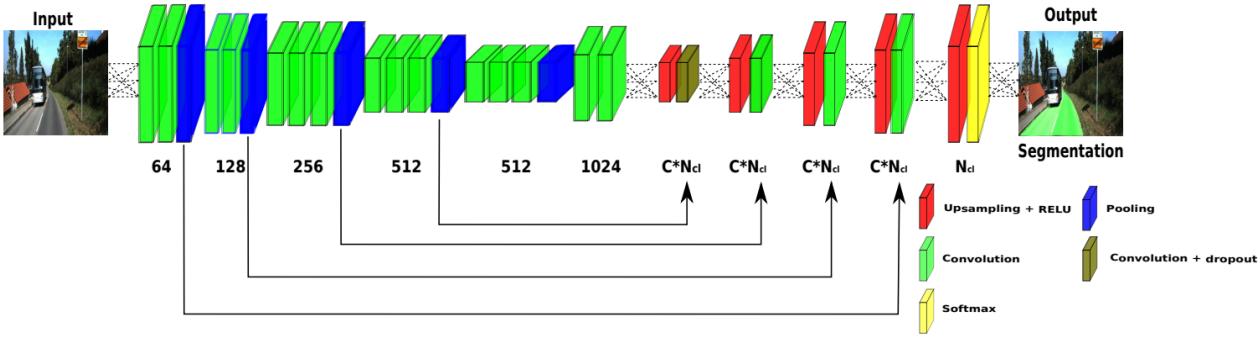
2.4 Training

We previously mentioned that what makes neural networks powerful are the sets of weights that can be modified in order to improve accuracy in the output. Training a neural network involves a training dataset paired with their *ground truth labels*. In the case of road segmentation, the ground truth labels come from manually segmented images in which people have hand-labeled the road and non-road surfaces. The images are provided to a neural network and the output of the network (class probabilities for every pixel) is calculated using forward propagation. For each pixel the highest class probability is compared to the known label and a *loss function* is calculated as the difference between the two. A high loss would indicate that the neural network have performed poorly in its task, while a low loss would indicate otherwise.

2.4.1 Backpropagation

Weights are initially randomized in the construction of a neural network. In the forward pass, an image from the training dataset is sent through the network and the output probability is compared to the true label probability provided with the test image. As mentioned above, this comparison is quantified using a loss function. Going backward through the network from output to input (called *backpropagation*), the network will evaluate which weight contributed the most to the total loss and calculate the weight adjustments that would minimize the loss. The loss function has its own curve and gradients. By aiming for the local minima relative to the weight, the network will produce the lowest loss. This process is called *gradient descent*. Another component we need to consider is the learning rate, or the amount by which to adjust weights while seeking the local minima. With a high learning rate, we cover more ground each step, but risk overshooting the minima. With a low learning rate, it is more precise, but time-consuming. After the weight calculation is completed at each layer, the weight will be updated using the calculation from the backward pass. The number of training examples in one *epoch* (forward/backward pass) is called *batch size*. In road segmentation tasks, the batch size could consist of hundreds of road scene images in one epoch. A large training dataset has the benefit of better fine-tuning the weights but requires

Figure 3: Up-Convolutional Network. The network part up to the first up-sampling layer the encoder side of the network and the following portion the decoder network side. Deconvolution layers have size equal to C $*$ N_{cl}, where N_{cl} stands for number of classes and C for the scalar factor of filters augmentation. The numbers under the convolution layers represent the depth. [5]



more memory. Therefore, the most optimal way of training a CNN for road segmentation task is usually via stochastic gradient descent (SGD). SGD is a method used during the training phase to reduce the amount of training required while keeping the network better trained by randomly picking samples from a training dataset to train the network.

2.4.2 Dropout

Neural network in general sometimes suffer from overfitting. It is condition in which the network is so well trained in the training dataset that it fails to generalize the underlying relationship, causing the network to do poorly in its prediction in the testing dataset. This could attributed to the fact that a few weights are trained and modified in the training phase, leaving the rest of the weights effectively deactivated. Therefore, neural networks commonly implements a dropout as a technique to deactivate a certain percentage of weights during the training phase. Doing so would allow the rest of the weights to be trained on the training set, thus allowing the network to better understand the underlying relationship of the dataset.

2.5 Fully Convolutional Network

The ultimate goal in road segmentation is that the output of the network has the same size and resolution as the input image with each pixel labeled as road or non-road. As we discussed in section 2.3.3, the pooling layer inside a CNN reduces the spatial dimension of the input in order to decrease the amount of parameters needed to be trained. Therefore, the end of all pooling and convolution layers results in a series of feature maps that are compressed. In order for the output to match the size and resolution, we need to return these feature maps back to the original input. Long, et al developed a type of CNN called fully convolutional network (FCN) that enables this functionality. An additional layer called deconvolution or up-sample layer is added to the end of a CNN architecture. The deconvolution layer takes in all the feature maps from previous layers and reconstruct the maps back to the size of the input. Another common option that is employed to reconstruct the feature maps back to the original input is through a process called max-unpooling. Max-unpooling preserves the location where the original max-pooling took the maximum value in the spatial extent considered for max-pooling and pad zeros to all the other empty location, essentially performing a reverse max-pooling operation. The FCN architecture could be generalized into two main components: *encoder* and *decoder*. The encoder consists of convolutional layers and pooling layers that extract features from images and reduce the spatial dimension. Meanwhile, the decoder recover the object details and spatial dimensions lost in the encoding component. [4]

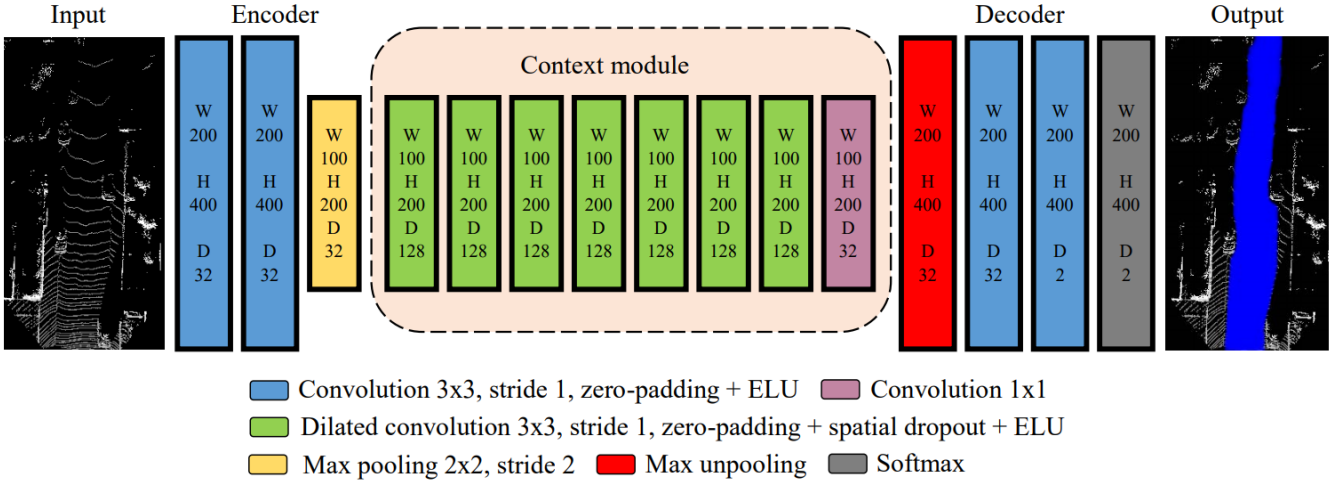
3. METHODS

Oliveira, et al [5] and Caltagirone, et al [2] approach the road segmentation task in two different ways. Oliveira, et al approached the road segmentation problem by creating their own modification of the FCN called Up-Convolution Network (Up-Conv-Poly). The Up-Conv-Poly takes in a color road scene image and outputs the same image with the road and non-road surfaces highlighted. Meanwhile, Caltagirone, et al approach the road segmentation problem with their own network called LIDAR-only Deep Neural Network. As the name suggests, it takes in LIDAR point cloud data. The point cloud data is initially 3-dimensional, but then is compressed down to a 2-dimensional grid image. The output is similar to the Oliveira, et al network output as it creates the same input image with each grid cell labeled as road or non-road surface.

3.1 KITTI Benchmark Dataset

The KITTI road benchmark dataset is designed to benchmark road detection. The dataset was acquired in various locations such as city, rural, and highway over a period of five different days. The dataset contains both a training set and a test set. The training and test set have each of its pixel already labeled as road or non-road surfaces that act as ground-truth labels. These ground-truth labels are obtained through manual segmentation of each road scene image. As mentioned in section 2.4, the training set is important during the training phase as it provides a way for the weights inside the network to be properly adjusted. The KITTI road benchmark consists of both road scene images and LIDAR point clouds as an extension to the data set. [2][5]

Figure 4: Architecture of the proposed LoDNN. The network has an encoder and a decoder but has an additional implementation of a context module. The input of the network is LIDAR point clouds compressed into 2-dimensional grid. The output has the same dimension and resolution as the input but with road surfaces labeled blue. W represents the width, H represents the height, and D is the number of feature maps. [2]



3.2 Up-Convolutional Network

Up-Convolutional Network takes a color road scene image and outputs a class score for each of pixel of the input image, thus labeling each pixel as road or non-road surface. The network like FCNs could be split into two parts, an encoder and a decoder. The encoder is responsible for dissecting the image for specific features and output a series of feature maps. The encoder part of the network is inherited from a network architecture called Visual Geometric Group (VGG), more information can be found in [7]. Meanwhile, the decoder part of the network adopted the up-sampling layers proposed by Long, et al. The decoder takes in the feature maps generated from the encoder and recreate an output that has the same resolution and spatial dimension as the input. The decoder consists of deconvolution layers that up-samples the features maps via bilinear interpolation. Bilinear interpolation could be summarized as a procedure for taking four data-points in a feature map and using them to construct a larger collection of data-points that brings the spatial dimension closer to the input image.

Dropout layer (discussed in section 2.4.2) is included in the Up-Conv-Poly to avoid overfitting. A convolution layer is implemented right after the up-sampling and convolution layer with the same spatial dimension as the previous layer. This layer is called a $1x1$ convolution layer that is designed to increase the amount of non-linearity that can be incorporated into the network [1]. Oliveira, et al also implemented a softmax layer (discussed in section 2.3.4) at the end of network. See figure 3 for a complete architecture design of the Up-Conv-Poly.

Researchers also implemented data augmentation to compensate for the small number of training examples. They employ a series of data transformations such as scaling and altering the RGB value of the original image, so that more training examples are available for the network to learn. Thus, increasing the accuracy of the prediction output by the network.

3.3 LIDAR-only Deep Neural Network

Caltagirone, et al developed a LIDAR-only Deep Neural Network (LoDNN) that takes LIDAR point clouds as inputs and outputs a similar result as Up-Conv-Poly. LIDAR point clouds are 3-dimensional point clouds information that needs to be transformed into a suitable format before it can be used as an input for the network. The first step of the procedure is to create a grid in the x-y plane of the LIDAR point clouds and compress the 3-dimensional information into the grid. For each grid cell, some basic statistics are the computed: number of points, mean reflectivity, mean, standard deviation, minimum and maximum elevation. These six grids, each representing an aspect of the original LIDAR point clouds, are then fed into the network.

Like Up-Conv-Poly, LoDNN follows an encoder/decoder configuration. Its encoder is made up of two convolution layers and one pooling layer. The output of the encoder are feature maps that are then passed on to the context module. Context module are made up of *dilated convolution layers* which are similar to regular convolution layers but have the receptive field for the filter increasingly expand at every subsequent dilated convolution layer. Expanding the size of the filter effectively expands the context for the filter which improves accuracy while still keeping the number of parameters down [2]. The activation function used by dilated convolution layers is called an exponential linear unit (ELU). A 1x1 convolution layer is implemented at the end of all dilated convolution layers to add some form of non-linearity into the network. The context module of the network is immediately followed up by the decoder component. The decoder contains a max unpooling layer, followed by two convolution layers and a softmax layer. The two convolution layers act as up-sampling layers bringing the feature maps generated from the encoder and context module back to the same spatial dimension as the input. See figure 4 for a complete architecture design of the LoDNN.

It was not appropriate to inherit a pretrained encoder

from a previous established network because the encoder would only be trained for camera images. Therefore, Caltagirone, et al deemed it more appropriate to train the network from scratch, using only KITTI training data.

Researchers also implemented data augmentation in their network. Each training images was rotated about the LIDAR z-axis for angles in the range [-30°, 30°] using steps of three degrees. After rotation, each example was also mirrored about x-axis. In this way, the training set was increased by a factor of 42. [2]

The output of the network has the same spatial dimension as input grid but with each grid cell labeled as road or non-road surface.

4. RESULTS

The two proposed networks were both evaluated on the KITTI road benchmark test set in the urban road category. Some metrics were used for evaluation such as recall (REC), precision (PRE), maximum F1-measure (MaxF), and time it took to make inference on a single image. Four important metrics are also needed to considered, true positives (TP), representing the road surfaces predicted by the network was accurate; false positives (FP), representing the road surfaces predicted by the network was inaccurate; true negatives (TN), representing the non-road surfaces predicted by the network was accurate; false negatives (FN), representing the non-road surfaces predicted by the network was inaccurate. Given the definitions of the four important metrics, we can now understand what precision and recall means,

$$Precision = \frac{TP}{TP + FP} \qquad \text{Recall} = \frac{TP}{TP + FN}$$

Precision is also a statistical term that determines how much of the road surfaces determined by the network was actually accurate out of all road surfaces determined by the network. Recall is a statistical term that determines how much of the road surfaces determined by the network was actually accurate out of all possible road surfaces in the input image. The maximum F1-measure is the harmonic average between the recall and precision. Table 1 illustrates the performance result gathered from both Up-Conv-Poly and LoDNN after running the road benchmark test set.

Table 1: KITTI Road Benchmark Results (In %) On Urban Road Category

Method	MaxF	REC	PRE	Time (ms)
LoDNN [2]	94.07	95.37	92.81	18
Up-Conv-Poly [5]	93.83	93.67	94.00	80

LoDNN outperformed Up-Conv-Poly in terms of the maximum F1-measure, precision and inference time, meaning LoDNN has a higher accuracy and was faster than Up-Conv-Poly in making predictions on new images. Caltagirone, et al did not explain the exact reason why LoDNN received a higher accuracy and less inference time. But judging from the differences in the network architecture and types of input, one might be able to deduce that LIDAR systems could ignore much of the background noises (shadows, light reflection, etc) compared to camera images. One thing to notice that Up-Conv-Poly did receive a higher precision in its network than LoDNN did. Although, no explanations were given as to why this has occurred. Thus, it propagated the effect to the network in which less work is needed by the network to make inference and increasing the accuracy of its inference.

5. CONCLUSION

As demonstrated by the work of Oliveira, et al. and Caltagirone, et al. neural networks show considerable promises in road segmentation in terms of their accuracy in predicting road surface and performance. Oliveira, et al. combined previous trained encoder from [7] and the up-sampling layers from [4] to create the Up-Conv-Poly. Meanwhile, Caltagirone, et al trained its own encoder and implemented a context module to increasingly expand the receptive field of its convolution layers, thus increasing the context considered by the filters. When comparing the performance of each network, the LoDNN came out ahead in terms of its harmonic average of precision and accuracy as well as its inference time of the KITTI road data set in the urban road category.

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