A Robust Method for Lane Detection under Adverse Weather and Illumination Conditions Using Convolutional Neural Network

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ABSTRACT

Every year thousands of people lose their lives due to traffic accidents. Road accidents, especially the ones on the highways are the most fatal ones. Accidents not only cut peoples' lives short but also cause intense financial loss to the country. Many people who survive disastrous accidents are often left with critical injury or paralysis. Particularly in Bangladesh majority of the drivers are minimally educated. They do not have sufficient knowledge and tend to ignore the traffic rules often. As a result the roads are filled with careless drivers. Consequently most of the accidents on the highways and city roads occur due to the lack of awareness of the drivers. Additionally, many of the roads are poorly lit which makes it difficult to drive in unfavorable weather. An autonomous lane detection system can play an important role as a solution to the problem by assisting the driver in seeing the lane clearly. It can also generate warning to the driver in case of an unintentional or incorrect change in lane to avoid accidents. The lane detection method can be further developed to traffic sign and pedestrian detection and eventually a self-driving vehicle. In this study a robust lane detection method using deep learning has been proposed which can detect lanes in various weather and lighting situations. The proposed system has been compared to other baselines in related field demonstrates high accuracy and real time performance.

CCS CONCEPTS

• Computing methodologies~Computer vision • Computing methodologies~Machine learning • Computing methodologies~Neural networks

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KEYWORDS

Artificial Intelligence, Machine Learning, Deep Learning, Computer Vision, Lane Detection, Adverse Weather

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1 INTRODUCTION

Traffic accident nowadays is one of the vital causes of death. A WHO survey [35] states that every year more than 1.25 million people lose their lives and 20 to 50 million people suffer from non-fatal injuries worldwide. In Bangladesh, more than 18000 accidents have occurred in the past three years which caused over 25000 deaths and more than 62000 injuries [36] and among these accidents 37% occurred due to reckless driving and 53% occurred due to over speeding. The report [36] also states that road accidents kill 20 people every day in Bangladesh and bring about 400 billion taka loss every year. Recent reports [37], [38], [39] show that majority of the accidents take place due to the lack of awareness and reckless driving. Accidents occurred on highways are more severe than accidents which are occurred in the city as the vehicles on highways travel at a high speed. Collisions with other vehicles on highway or veering off the highway result in fetal injuries in most cases. Side impact collision is one of the common types of collision which occurs when a driver changes road lane unintentionally [1]. This type of lane change occurs due to several reasons like lack of awareness or drowsiness of the driver.

Human beings can detect the road lanes accurately under any driving scenario. At the same time they have a disadvantage of not always being careful and conscious of driving. On highways many drivers become drowsy and tired due to driving monotonously for a long period of time which increases the chance of having an accident either by colliding with another vehicle or drifting off the road. Computers, on the other hand, do not suffer from the issue of drowsiness and lack of awareness. If a computer can be integrated with a vehicle to detect the lanes on the road and identify other objects the risk of road accidents will get reduced to a great extent. A computer system can not only detect lanes and objects on the road but also can read the road signs and provide feedback to the driver in any dangerous situations such as proximity to another vehicle or drifting off the lanes.

Many studies [1] – [30] have suggested that integrating driving assistance system will improve driving safety. Lane detection is one of the core features of driving assistance system. It identifies the road lane on which a vehicle is travelling. It can aid the driver in keeping the vehicle on the lane [1] – [30]. Several other studies [1], [3], [7], [10], [14] – [17] have been performed suggesting a lane departure warning system along with lane detection which can detect unintentional lane changes and notify the driver via a feedback system. This methods can bring down the rate of accidents due to unintentional lane changes. Thereby, this research presents a machine learning based lane detection method which can detect the road lanes in different weather and illumination conditions.

2 RESEARCH BACKGROUND

There are numerous method in lane detection, some are based on computer vision based methods while some are based on LIDAR based methods. In computer vision based lane detection a camera is installed on the back of the rear view mirror of the car. A video feed is taken from the camera and passed to a computer. The computer extracts the image frames from the video and run the computer vision techniques on each frame to detect the lanes.

Hough Transform (HT) has been a popular choice for detecting lanes among other feature segmentation. Color based segmentation methods have been the least popular of all as the color based methods are sensitive to illumination changes [25], [26]. Basically, HT is a line detection algorithm in an image. Lanes on the roads are considered as lines and using HT the lanes are detected. Initial works include Gaikward et al.[1], Bhujbal et al.[3], Kortli et al.[7] and Amaradi et al.[11] who utilized HT to detect lanes. All of them achieved detection accuracy over 90% but those were mostly for straight lanes and constant weather condition. HT also is a computationally expensive process and requires high memory space [9]. To overcome this issue Yi et al.[2], Lotfy et al.[10] and Peng et al.[28] modified the HT to make it more computationally inexpensive. Son et al.[5], Kortli et al.[7], Sun et al.[25] and Chin et al.[26] implemented color based lane detection method among which Son et al.[5] and Kortli et al.[7] achieved more than 90% accuracy in good weather conditions but it dropped considerably as the weather changed. An improved RANSAC based lane detection method was implemented by Guo et al.[4] which could detect both straight and curved lanes. Several researches were performed to improve the detection of missing or occluded lanes. Jung et al.[8] and Yenİaydin et al.[13] implemented lane detection methods based on spatial-temporal images and reliable lane marking respectively which could detect the missing or worn off lane markings. Another method name “SafeDrive” was invented by Sattar et al.[12] who detected the lane marking under poor lighting conditions. They relied on the vehicle’s location data to retrieve other clear images of roads on the same location and then detected the lanes on those images. Nguyen et al.[14] performed another study which was able to detect lanes under various weather situations given that the lane marking are solid and clearly visible. Ambarak et al.[17], Wang et al.[18], Ye et al.[19], Kim et al.[20], Chen et al.[21], Zhang et al.[22], Neven et al[23], Huang et al.[24], Shi et al.[29] and Li et al.[30] utilized machine learning approaches to detect the lanes. Among them Ye et al.[19], Kim et al.[20], Chen et al.[21], Zhang et al.[22], Huang et al.[24], Shi et al.[29] and Li et al.[30] used convolutional neural network for detecting lanes. Machine learning based systems showed high accuracy and low computational cost which made it suitable for real time usage. Zhang et al.[22] combined both convolutional neural network and recurrent neural network reduce the computation time even more. Huang et al.[24] combined spatial-temporal images and deep learning algorithm which made their system more robust under various environmental scenarios.

Most of the traditional computer vision based methods [1] – [5], [7], [9] – [11], [13] and [14] shared the similar framework which only varied on different methods in each step. Guo et al.[4] implemented an improved RANSAC algorithm combined with least square method to fit the lanes which improved their real time performance. Son et al.[5] Lotfy et al.[10] also utilized least square method for fitting lanes. Hajjouji et al.[9] used HT with CORDIC for lane detection and Kalman filter for lane fitting. Yenİaydin et al.[13] obtained a bird’s eye view of the road by implementing an Inverse Perspective Mapping (IPM) on the ROI which made their computation cost lower. Nguyen et al.[14] have detected vanishing point of the lanes to generate ROI and then used EDLanes algorithm to detect and fit lanes. EDLines improved their computation time and reduced the rate of false detection. Wang et al.[18] used an encoder-decoder based neural network which could detect lanes under various weather conditions. Convolutional Neural Network (CNN) have become immensely popular in lane detection. Majority of the frameworks for lane detection uses CNN. Kim et al.[20] has combined both computer vision and machine learning technique. If the road scenario is simple they used RANSAC for lane detection and used CNN to detect lanes in complex road scenarios. Neven et al.[23] used one encoder-decoder based neural network to detect the lanes and another neural network for clustering and curve fitting on the detected lanes which made their detection robust and at the same time computationally expensive.

Authors who implemented traditional computer vision based techniques also acquired higher accuracies in specific scenarios. Gaikward[1] implemented their framework on MATLAB and achieved an accuracy of 97% for videos taken from cars which were travelling between the speed of 30 and 120 km per hour. Yi et al.[2] achieved higher accuracy for larger image size and their accuracy fell with the reduction of input image resolution. Bhujbal et al.[3], Guo et al.[4], Kortli et al.[7], Amaradi et al.[11], Ambarak et el.[17] and Ye et al.[19] also implemented their frameworks in MATLAB. Bhujbal et al.[3] and Kortli et al.[7] obtained average accuracy 94% but their image resolution was low, 240 x 320, which is certainly an issue as lower image resolution can increase the rate of false detection. Guo et al.[4] used image of 480 x 856 having its accuracy ranging from 86% to 93% and an increase in false detection rate under complex scenarios. Many researchers also implemented their systems on embedded device. Lotfy et al.[10] implemented their system on an ARM Cortex A7 and A15 microcontrollers and Wang et al.[18] implemented their system on NVIDIA Jetson TX1 GPU and on PC with NVIDIA Titan xp GPU. Running time for NVIDIA Jetson was 26 fps and 33 fps for PC. Ye et al.[19] implemented their method on PC with Intel core i3 CPU and 8 GB RAM without any GPU and it ran at ~8 fps. Chen et al.[21] used Caffe framework with NVIDIA GTX 1080 GPU to implement their system and acquired around 84% accuracy while Zhang et al.[22] used Keras with the same GPU and achieved over 95% accuracy on their system. Neven et al.[23] also used the same GPU achieving an accuracy slightly over 96% and their running time reached 19 ms/frame. Huang et al.[24] implemented their method on NVIDIA TX2 embedded platform. They tested their dataset on CalTech lane dataset [32] and TuSimple Benchmark dataset [33]. Their accuracy ranged between 93% and 98% for different datasets.

3 PROPOSED METHODOLOGY

The following section presents the method that has been implemented to develop a lane detection system.

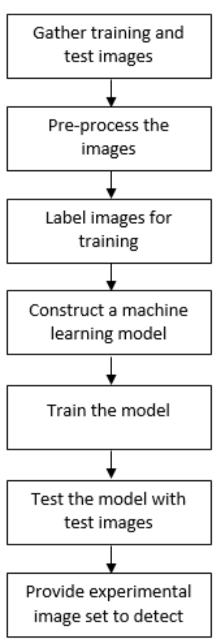

Figure 1: Proposed Lane Detection Method Based on Deep Learning

3.1 Gathering Training and Test Images

Machine learning approach requires an enormous number of training images. In case of this study, thousands of images of road lanes under different weather and lighting conditions are needed to train the computer. It is fairly difficult for an individual to generate this dataset. Fortunately a few open source datasets are available. For this research the training dataset has been acquired from TuSimple Lane Detection Benchmark [33]. The dataset has over 40,000 images of various environment, weather and lighting scenarios. The images were generated from videos taken from car camera. The dataset also provided lane ground truth for 3626 frames of images.

3.2 Pre-processing the Images

Pre-processing step usually consists of some image processing techniques to enhance or de-noise the image. In this research the images taken from the video were converted to grayscale. The grayscale conversion reduces the number of color channels from 3 to 1 which reduces the computation cost as well. Next the images were subjected to Gaussian filter for removing any noise from the images. Then the images were scaled down and the Region of Interest (ROI) was selected. ROI crops off a section of the image and only keeps the portion that is required to perform the operation. This reduces the computation cost as the computer does not have to scan the unnecessary portions of the whole image. After that, perspective mapping, a geometric transformation, was performed on the image to generate a bird's eye view of the road plane. Generating a bird's eye view makes it easier to run the algorithm to detect the lane lines. After the detection of the lanes the bird's eye view image is transformed back to its original form.

3.3 Labeling the Images for Training

The research is based on supervised machine learning. In supervised machine learning, the computer is fed with input and output data corresponding to the inputs. It tries to learn the outputs for each of its input through a learning algorithm. As in this case, road images are being fed to the computer as inputs, for training the computer, the outputs or the lanes also needs to be fed to the computer. In order to do that the TuSimple Lane Dataset [33] was utilized. They provided lane coordinates of lanes for 3626 images. These images were fed to the machine learning model to train the system. A sample lane label for ground can be observed in figure 3.6. In this research the lanes have been considered as curves and the equation of a curve can be represented by the following polynomial expression:

$$y = ax^2 + bx + c \qquad (1)$$

There are three coefficients in one equation of a curve. This research focuses to only detect the lane on which the car is presently driving and avoiding the rest of the lanes. To find out the current lane two polynomial equations are needed as there are two lane marking for each lane. Therefore, the system has to find out total six coefficients, three for each lane marking. These labeled images are fed to the computer along with the raw image and the computer learns to find out the equations to represent the curves for all of the training images using a machine learning algorithm.

3.4 Development of CNN Algorithm

In this research, a supervised learning method is selected due to its simplicity and less computation cost compared to the other types. There are numerous methods to implement a supervised learning model. Among them the convolutional neural network or CNN is very popular for image based applications. It is one of the most effective machine learning approach to do image recognition, image classification and object detection. Convolutional Neural Nets take in images as input, attempt to decipher different small features about the images regardless of their position using a series of mathematical operations such as convolution, pooling in order to understand the full picture of what's happening. These mathematical operations pertain to modeling an image as series of numbers with each number representing pixel density. Convolutional Neural Networks were inspired by research done on the visual cortex of mammals and how they perceive the world using a layered architecture of neurons in the brain.

An encoder-decoder based CNN has been implemented to detect the lane lines in road images. An encoder-decoder based CNN is a type of CNN where input image goes through several convolutional steps and then again several de-convolutional steps. The reason for this is in cases of object detection the network has to detect the object, in this case the lanes, and map it on the actual input image. Now after each convolution, the image size is reduced for reducing computation time. As a result the resultant image after the convolution has to be restored to the actual size. That upscaling of the image step is known as de-convolution. This model does not include a fully connected layer as there is no classification operation present. The proposed CNN model is shown in Figure 2.

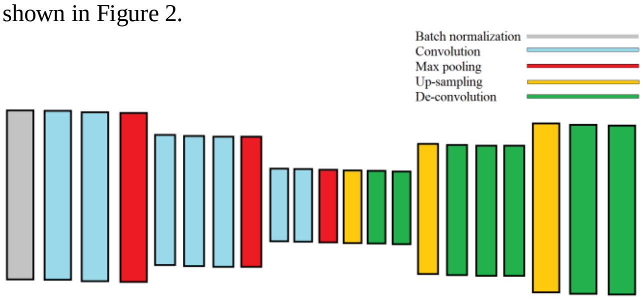

Figure 2: The Proposed CNN Model

The input image goes through these steps: Batch normalization, Convolution, Max pooling, Up-sampling and De-convolution. Batch normalization means scaling and adjustment of the input values on the scale of 0 to 1. Each convolution layer is followed by a ReLU activation function. The model takes the training images and the ground truth images as input and on the output it produces the six coefficients for the two lane lines.

3.5 Training the Model

The training process of a CNN is described here. First the input is passed to a convolutional layer. A feature detector kernel generates a feature map of the input by performing convolution operation on the input with the kernel. The output of the convolutional layer, the feature map, is then passed to the activation layer. The activation layer activates if the desired feature is found on the feature map otherwise it remains deactivated. Next the output of the convolution layer is passed to the pooling section where the feature map is reduced in size to minimize computation time. The reduced feature map is then passed to the next layer of convolution. Finally, the outputs of all of the activation functions are then passed to a fully connected layer where a predicted output is generated for the given input. Then this predicted output is compared to the actual output and error, the mismatch between the predicted output and the actual output, is calculated. This error is called the loss function which defines the quality of the prediction. There are many methods to calculate the loss function. The most popular of them are Mean Squared Error (MSE), Gradient Descent (GD) and Stochastic Gradient Descent (SGD). Next, the error is fed back to the summing junction of the convolutional layer via a backpropagation algorithm. In the summing junction an optimizing algorithm re-adjusts the values of the kernel in the convolutional layer with respect to the loss function. This process continues until the error reduces significantly and the predicted output matches the actual output.

3.6 Testing and Evaluation of the Model

After training the network test images are given to the network to assess the accuracy of the network. Once the network performs well in the test images it is given real world images as inputs which are considered as validation set and performance is observed.

4 EXPERIMENT AND RESULT

The methodology described in chapter 3 has been implemented on a PC with Intel core i7 processor, 8GB of RAM and NVIDIA GeForce 940MX GPU with 4GB of memory. For implementation, Keras was used with Tensorflow backend. The detailed experimental setup and result analysis are discussed in the following sections.

4.1 Experimental Setup

The details of the experiment are described in the following sections.

4.1.1 Input Data Preparation

For training the network the training images and corresponding output must be fed to the network. The input images were scaled down to a resolution of 80 x 160 and stored in an array and so was the labels. The labels were normalized to a scale of 0 to 1. Before sending the images to the network the images were pre-processed.

4.1.2 Network Parameter

The convolutional neural network designed here has the following parameters –

Number of convolutional layers = 7
Number of pooling layers = 3
Number of up-sampling layers = 3
Number of de-convolution layers = 7
Shape of the convolutional kernels = 3 x 3
Shape of the pooling and up-sampling layers = 2 x 2
Batch size = 128
Number of epochs = 10
Activation function = Rectified Linear Unit (ReLU)
Optimizer = Adam
Loss function = Mean Squared Error (MSE)

4.1.3 Experimental Procedure

After the model was trained and tested real world data was given to the model. As input, HD video files having resolution of 720 x 1280 pixels were given to the system. The system first extracted all the frames of the video file and using the trained model it fit lanes to each of the extracted frames. Once the fitting of lanes were completed the system compiled all of the lane detected image frames to another video file as output. For experiment, the video files were taken from Dhaka-Chittagong highway at different times and under different lighting conditions. Some of the videos were taken from the internet and some were shot while driving.

4.1.4 Generating the Lane Coefficients

The CNN designed here does not have a fully connected layer. Rather the CNN outputs the six coefficients of the two curves that represent the lanes. The CNN produces six coefficients for each of its input image. The initial predictions contains high error and as the network learns the error gets reduced with the increased number of iterations. The model trained with the coefficient is then used on the test set and validation set to predict the coefficients of the curves of lanes. These coefficients are then fit over the images to predict the lanes.

4.1.5 Error Estimation of the Network

The above figure shows the reduction of error rate with respect to number of iterations. As it can be seen the initial loss or error was significantly high at 70%. Gradually with training the error rate decreased and after 10 epochs the error rate reached to 0.44% on train set and 0.46% on test set which is very close to zero.

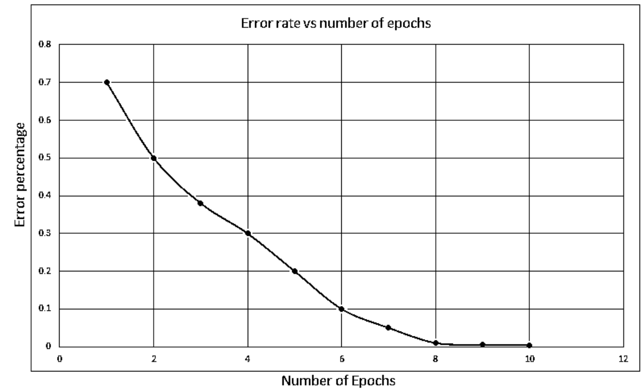

Figure 3: Error Calculation of the Network

4.2 Experimental Result

For experimentation purpose videos were captured on Dhaka Chittagong highway with under various weather and lighting conditions. The weather conditions are:

1) Clear daylight
2) Exposed sunlight
3) Clear and worn off lanes
4) Straight and curved lanes
5) Foggy morning
6) Foggy night
7) Night with poor lighting
8) Rainy day

The proposed method and developed framework has been tested on all of these videos. The results of the lane detection on these videos are given below –

Figure 4: Lane Detection on a Clear Weather Condition

Figure 5: Lane Detection under Exposed Sunlight Condition

Figure 6: Lane Detection on Foggy Morning

Figure 6: Lane Detection on Foggy Night

Figure 7: Lane Detection at Night with Poor Illumination

Figure 8: Lane Detection on Rainy Day

4.3 Comparison with Other Methods

Table 1 presented a comparison of the proposed method with three other state-of-the-art methods of lane detection. From the comparison it is clearly understood that the proposed method has high accuracy and it can detect lanes in many of the unfriendly environments.

Table 1. Comparison of Result with Other State-of-the-art Frameworks

Method	Platform	Accuracy	Environments	Running Time
Spatial-Temporal Based Lane Detection [24]	NVIDIA TX2	98%	Day, night, rain, snow, straight and curved lanes, complex illumination	30 fps
Lane Detection based on Instance Segmentation Approach [23]	PC with NVIDIA 1080 GPU	96%	Day, good and medium weather	52 fps
Lane Detection based on Structural Analysis [19]	PC with Intel i3 CPU and 8 GB RAM	98%	Day, night, straight and curved lanes	8 fps
This method	PC with NVIDIA GeForce 940MX GPU	98%	Clear daylight, exposed sunlight, night, straight, curved and worn off lanes, fog, rain, complex illumination	22 fps

5 DISCUSSION

This research started with an objective of lane detection of roads due to its enormous importance. Lane detections are not only required for keeping the vehicle on the right lane but also to reduce the occurrences of road accidents and to develop autonomous vehicle. Lanes can be detected in many ways but the most efficient approach is based on machine learning as machine learning based approaches make the system learn and make sense of the environment. The convolutional neural network, a deep learning framework within the scope of machine learning, has gained popularity among the researchers for machine learning based on images such as image classification, object detection etc. A convolutional neural network based system to detect lanes has been implemented in this research. The implemented work has been tested and experimented in different scenarios to analyze the performance of the system and it has found to be satisfactory in many different conditions.

5.1 Contribution of the Research

The contribution of the research is manifold. Firstly, it will contribute socially by reducing the number of road accidents that occur each year and saving the lives of thousands of people. Secondly, it will save the tremendous amount of financial loss that the country has to go through each year due to the damages caused by road accidents. Thirdly, it is a significant scientific achievement that can be applied to develop advanced and autonomous driving or driver assist system which will not only bring safety to driving but also comfort to the driver.

5.2 Advantage over Existing Methods

The proposed method has a number of advantages over the existing methods. Most significant of them being that this method can identify lanes on more complex scenarios than the other methods. Secondly, this method exhibits real time performance with significantly higher frame rate. Other methods also have higher frame rate compared to the proposed method but they are all embedded platforms designed solely to perform machine learning computation whereas the PC has to perform other tasks as well. Thirdly, the input video frame has HD resolution and the lane is mapped on the HD video which makes it clearer to observe from a video screen.

5.3 Limitations of this Method

Although the method proposed in this thesis performs well in many scenarios it has some limitations as well. First of all, the system fails to detect the lanes if the camera is unstable. For precise lane detection the camera needs to be stable. The system suffers to detect lanes in areas where the roads are not smooth or bumpy. Secondly, the method suffers from excessive error in cases during night time when other vehicles approach from the opposite side and headlights of other approaching cars exposes the scene with glare. In this type of situation the method fails to detect the lanes. Thirdly, the method misses the detection of lanes if the lanes are too much worn off, meaning that the lane markings disappear from the roads for a longer distance. Lastly, this method can only detect lanes and it is not upgraded to a lane departure warning system or a lane keeping assist system.

5.4 Future Work

This research has valuable future prospects. The current system can be merged with other machine learning algorithms such as Recurrent Neural Network (RNN) which has a short time memory and can upgrade their prediction by analyzing their past experience. Integrating RNN with the current system might bring solution to the problem of glare exposure discussed in the previous article.

Camera stabilization and geometrical analysis should be performed to solve the camera stability issue. That will improve the detection process more robust.

The system developed can be implemented in the vehicles to design a lane departure warning and a lane keeping assist system. In future, this research can be augmented to not only lane detection but also detection of other objects on the road such as other vehicles, road signs and pedestrians. These achievements can lead the research to the development of fully autonomous car.

6 CONCLUSION

In this research a lane detection system has been developed by using deep learning techniques and curve fitting estimation. A lane is considered as a curve and the equation for that curve is expressed with a polynomial equation. This polynomial equation has been predicted by the CNN to fit the lane on the video frames. The estimation of the polynomial coefficients reduced the computational complexity and at the same time made the system more robust. Experiments were done under various environmental situations and satisfactory results were found. In future, the extension of the current method to other architectures of machine learning may increase the robustness of the system even more.

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