A layered approach to robust lane detection at night

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A Layered Approach To Robust Lane Detection At Night

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***Abstract*— A novel approach towards detecting lanes at night using a video camera is presented in this paper. At first, the image is cropped and then converted to binary using an adaptive threshold. The novelty of the layered approach includes: i) the temporal blur, ii) low resolution Hough transform, and iii) iterated matched filtering. The developed system shows good performance when tested on real-world data that contains fluctuating illumination and a variety of traffic conditions.**

I. Introduction

DRIVER safety has always been an area of interest to research since driver distractions account for numerous accidents on highways. In multiple studies performed by the National Highway Traffic Safety Administration (NHTSA), it was shown that over 20% of the accidents are due driver distractions. Further analysis showed that ≈ 60% of these accidents were caused by drivers who were either talking on the phone, adjusting GPS devices or tampering with the CD player [1], [2], [3]. The high fatality rate has prompted industry and academic institutes to focus on embedding smart systems in the automobile that can aid a driver during a commute.

With the increased speed and smaller sizes of complex electronics, intelligent devices are beginning to be integrated into vehicles giving rise to Driver Assistance Systems. Driver Assistance System (DAS) is a synonym for an intelligent system that is a means of providing assistance to the driver. DAS include GPS devices, cruise control, automatic transmissions, anti-lock brakes, traction control etc. This document focuses on lane detection, which is also a form of a Driver Assistance System [4].

Lane detection is the process of locating lane markers on the road and presenting these locations to an intelligent system. The applications of a lane detecting system could be as simple as pointing out lane locations to the driver on an external display, to more complicated tasks such as predicting a lane change in the immediate future in order to avoid potential collisions with other vehicles. Some of the interfaces used to detect lanes include cameras, laser range images, LIDAR and GPS devices. The proposed method relies on the use of cameras to accomplish the task.

This paper is organized as follows. First, prior work on lane detection systems is briefly reviewed, and the shortcomings of these systems are described. Then, the new system is introduced and explained. Light is then shed on the data collection and testing procedures. This is followed by the results section that shows some examples in which the system performs successfully, and a few scenarios where it fails. Finally, the conclusion and future work is presented.

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II. Prior Work

Numerous techniques have been developed to detect and extract lanes in an automobile. One the most common approaches is to compute the Hough transform to find straight lines in an edge detected image [5], [6], [7], [8], [9], [10], [11]. For example, in one system the edges are detected using a Canny edge detector, and the Hough transform is then computed to find the best fitting pair of lines corresponding to traffic lanes. One of the problems with this approach is that artifacts on the road, such as navigational text, arrows, cracks, and tar patches will often have features that appear to be straight lines in the edge detected images. In these cases, the Hough transform may incorrectly classify some of these artifacts as being the best candidates for lanes.

The ?Middle-to-Side? strategy is another variation of using edge detected images to find lanes [9], [12], [13], [14]. In this approach, the search for a lane marker pixel begins in the middle of image and the search moves outward until the first non-zero (edge) pixel or positive/negative gradient pair on both sides is found. This approach is repeated from the bottom of the image to the top [12], [14]. While the ?Middle-to-Side? technique shows promising results on structured and well-maintained roads, the problems with artifacts described above are more prominent. The reason for this is that some of the artifacts may be closer to the middle of the image than the actual lane marker edges causing a mis-detection. In addition, on highways with dashed lane markings, the Middle-to-Side approach may lead to unpredictable results.

When color cameras are used for lane detection, the color images are generally converted to a grayscale image using color transformations as shown in [15]. However, in [16], [17], [18], [19], lanes are detected by applying linear operations on the individual color channels. In [18], segmentation via chroma differencing between the various color channels is proposed whereas in [17], [19] RGB images are converted to a custom color space and [16] converts RGB images to an intensity independent color space such as HSI in hopes of making lane detection easier. Problems with color segmentation arise when the illumination has a non-white color such as yellow or amber that is found in most street lights. The non-neutral colored illumination can affect the camera?s perception of the lane markers and, as a result, causes them to possibly fall outside the required thresholds.

Finally, in [19] a fixed range of intensities is assumed for the intensities corresponding to the road and lane markers. However, intensity values are unlikely to remain consistent over the different construction materials used to build the road.

In addition to vision systems, sensors such as GPS and laser range images have also been used to detect lane marker locations. For example, [20] suggests using GPS with digital maps to determine the position of the vehicle with respect to the road and extrapolate the lane marker locations. GPS enabled devices are restricted to operation under an open sky, and require having up to date digital maps. GPS devices are also prone to errors of up to a couple of feet thereby making their use in lane detection of questionable utility. Laser range images have also been used to estimate lane boundaries on European roads [21], [22]. The detection of small reflective posts along the side of the road allow determination of the boundaries of the road. Similar to the GPS approach, lane marker location can be extrapolated from the boundary locations. These reflective posts are installed every 50m allowing them to be visible into the distance. The idea of using laser range images to detect lanes assumes the operation on single lane highways [21], [22] or on multi-lane highways with no traffic to prevent nearby vehicles from unintentionally blocking the line of sight of the range sensor.

Some of the popular lane detection techniques such as ALVINN [23], [24], LANA [25], and GOLD [26] that incorporate the use of neural networks, frequency domain features and binary morphology respectively have been cited to work well only on the data that they have been trained on, which raises questions about their robustness [27]. As a result, there is still scope for improvement as robust lane detection remains an unsolved problem.

III. Lane Detection System

The lane detection system presented in this paper is made up of a cascade of algorithms as illustrated in Fig. 1. Each of the blocks in this system are described below.

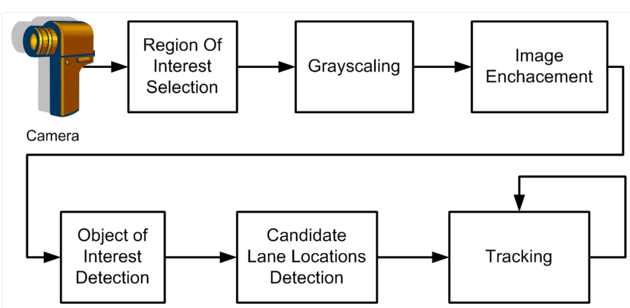


Fig. 1: Model of the proposed lane detection system

A. Cropping

The first step is crop out a Region Of Interest (ROI) in the original image in order to remove irrelevant objects such as the sky, street lights, signs, moon, etc. from the image. Cropping also enhances both the speed and the accuracy of the lane detection system. The speed improvement comes from the reduction in the size of the image to be processed whilc the improvement in accuracy comes from the elimination of objects outside the ROI that may have features similar to lanes as shown in Fig. 2. The ROI is set manually in this implementation; however, camera calibration parameters could used to automatically determine a suitable ROI.

(a) Original image with ROI in yellow

(b) Cropped image

Fig. 2: Images before and after cropping

B. Pre-Processing

The only pre-processing used in this lane detection system is the conversion of a color image into a gray scale image; as a result, monochrome images can bypass this stage. Assuming that the available color image is in Bayer format, it is first demosaiced to retrieve the color of each pixel. A simple color averaging scheme given by

$$\hat{I}(x, y) = \frac{Red(x, y) + Green(x, y) + Blue(x, y)}{3} \quad (1)$$

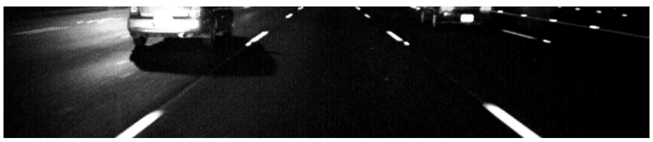
is then used to convert the color image to intensity where $Red(x, y), Green(x, y), Blue(x, y)$ are the red, green, and blue values of the pixel at location (x,y) and $\hat{I}(x, y)$ is its resultant intensity of the pixel at (x,y). Alternate methods of gray scale conversion can be found in [15].

C. Temporal Blur

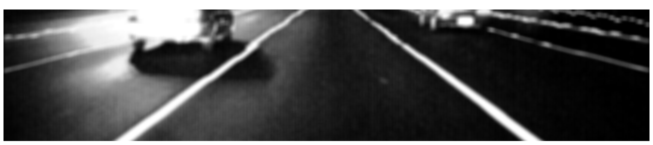
For lane detection, the shoulder lane of the road is generally easier to detect compared to a traffic lane since the shoulder generally shows up as a long and straight line in the image. Traffic lanes on highways are dashed lines and, depending on the exposure time, they may appear as a dot or a short line in the image. Temporal blurring may be used to extend the traffic lanes and give the appearance of a long and continuous line. The temporal blurring that is used is given by

$$AverageImage = \sum_{i=0}^{\infty} \frac{Image[n - \Delta i]}{N} \tag{2}$$

where $Image[n]$ is the image in frame n and Δ is the step size between the frames used in the averaging. The values of i and Δ should be chosen so that the temporal component of the blurred image is only a few milliseconds to avoid ghosting due to motion blur. Fig 3 shows the before and after effects of the application of the temporal blur. As expected, the dashed traffic lanes in Fig. 3a appear to be continuous in Fig. 3b. In addition, the blurring technique helps to reduce noise in the image assuming the presence of zero mean gaussian noise. Problems were anticipated in using



(a) Image before temporal blurring



(b) Image after temporal blurring

Fig. 3: Before and after effects of the temporal blur

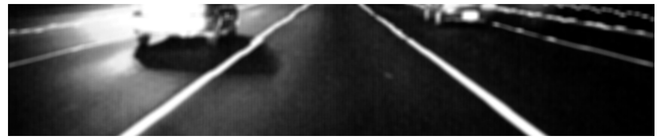
the temporal blur during a normal lane change maneuver; however, the lateral speed of the vehicle is much slower than its commuting speed. Consequently, the lateral distance covered within a few milliseconds is also very small. As a result, the width of lane markers is negligibly affected after blurring. Similarly on curving roads, the curvature of the road changes gradually as opposed to being abrupt. Therefore, lane markers are only slightly affected at the entry and exit points of the curve.

D. Adaptive Local Threshold

The adaptive threshold is used to extract the lane markers in the average image. Compared with a global threshold, the adaptive threshold varies depending on the characteristics of its neighborhood pixels [28]. This proves advantageous as isolated bright objects like street lights and taillights of cars would affect the global threshold, the adaptive method in general would not be easily skewed. The pseudocode for the adaptive threshold algorithm is given in Algorithm 1.

E. Candidate Lane Locations

Initially, the binary image obtained by applying the adaptive threshold is split into its left and right halves as illustrated in Fig. 5. Then, a low resolution Hough transform is



(a) Image with temporal blur

(b) Blurred image with applied threshold

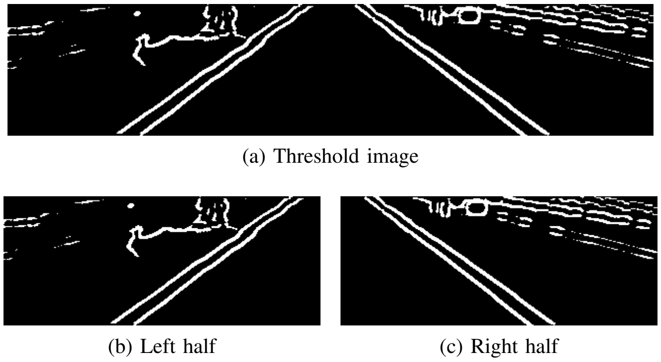
Fig. 4: Before and after effects of the adaptive threshold

Algorithm 1 Adaptive Threshold

$minrange = 255/10$
  /*Minimum likely difference between the lane markers and the road*/
for (Each Pixel) **do**
  $P0 =$ Actual pixel value
  $Q0 =$ New pixel value after threshold
  $min =$ Minimum value of neighborhood around P0
  $max =$ Maximum value of neighborhood around P0
  $range = max - min$;
  if ($range > minrange$) **then**
    $T = (min + max)/2$;
  else
    $T = max - minrange/2$;
  end if
  if $P0 > T$ **then**
    $Q0 = 255$;
  else
    $Q0 = 0$;
  end if
end for

computed on each half image to find the locations of straight lines corresponding to lanes. The low resolution implies using a larger step size for the iterations in (ρ, θ) space e.g. using $\Delta = 2.5$ rather than $\Delta = 0.25, 0.5...$ in addition to imposing a range restriction on θ. This idea is elaborated in Fig. 6 where Fig. 6a shows a full and dense iteration of the (ρ, θ) space in comparison to Fig. 6b, which is coarse and windowed. It is assumed that the vehicle is traveling within the lane so that each lane marker will appear in one of the two half images. Consequently, only one lane marker set needs to be found in each half image. This assumption will not hold during a lane change when the two lane markers may exist in the same half image. The angle restriction on θ helps to detect and extract the lane makers deemed appropriate for the particular half image.

The low resolution method allows for a fast and fairly accurate computation of the Hough transform. Upon its computation, the locations of X highest scoring lines are recorded. For illustration, one of these X lines is shown in



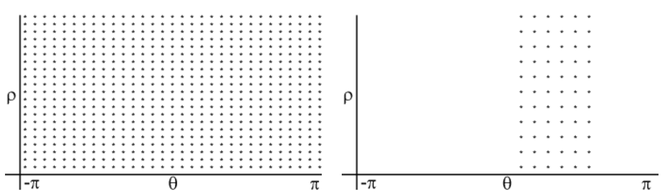
(a) Threshold image

(b) Left half

(c) Right half

Fig. 5: Threshold image with its corresponding halves

red in Fig. 7b. The binary image is then discarded as further processing is performed on the average image. The line in Fig. 7c is then sampled along its length into a finite set of points designated by ”+” as shown in Fig. 7d. A 1-D search window centered these at each of these discrete locations is created for use with a matched filter. The windows are represented by the horizontal red bars in Fig. 7e.



(a) High resolution

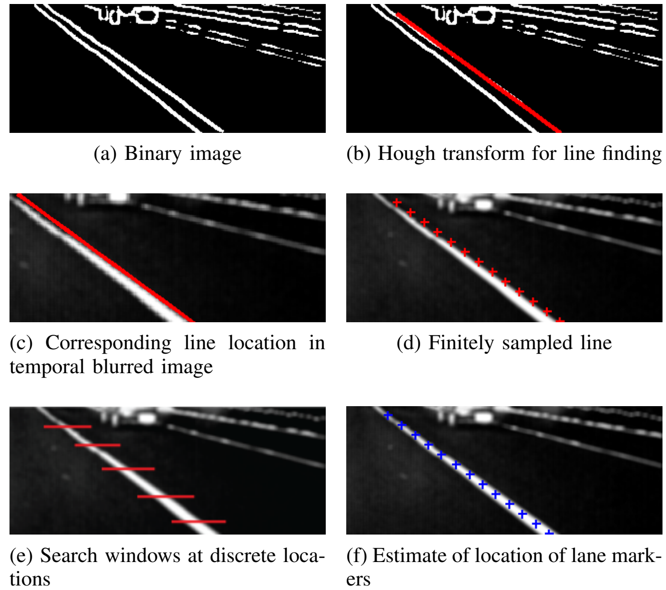
(b) Low resolution

Fig. 6: Difference in resolution of iterations in the (ρ, θ) space

A gaussian kernel is then used with the matched filter since the intensity profile of a lane marker in the search window resembles a noisy gaussian as shown in Fig. 8. The variance of the kernel increases as the filter iterates from top to bottom at the different search window locations. The increase in variance is to account for the increasing width of the lane markers as seen from the camera's perspective. Matched filtering is similarly performed on the remaining $X-1$ lines. Upon completion of the sequence of filtering, a book keeping strategy is used to determine the best estimate of the lane marker within each window as shown in Fig. 7f. With the estimates determined in Fig. 7f, lane detection is almost complete.

The final stage is to find the best fitting straight line through all these points. In Fig. 9b, the Hough transform is used to accomplish this task. The simple solution of ”Connecting the Dots” was not considered as outliers would cause the appearance of the lanes to have a jagged shape. Hough transform is also opted for over Least Squares Line Fit because the it is less affected by outliers.

Lane detection is similarly performed on the left half image. A custom implemented tracker is used improve results of the lane detection system.



(a) Binary image

(b) Hough transform for line finding

(c) Corresponding line location in temporal blurred image

(d) Finitely sampled line

(e) Search windows at discrete locations

(f) Estimate of location of lane markers

Fig. 7: Candidate lane location finding procedure

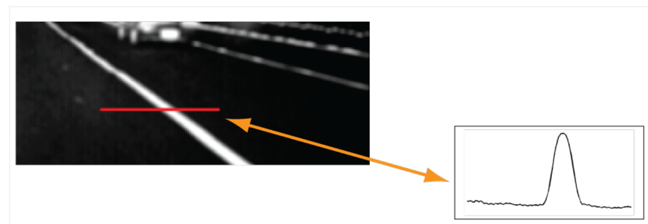
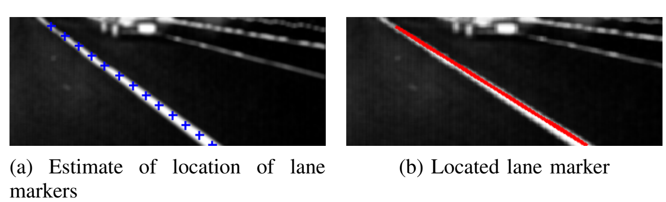


Fig. 8: Intensity profile of a lane marker in a search window

IV. Results and Analysis

A custom built Intel based computer and DC→AC power supply are installed in the trunk of a vehicle. Removable SATA 3Gbps hard disks allow portability of the captured data. A touch screen monitor allows the driver to interact with the computer. Video is captured using a Firewire S400 (400Mbps) color camera in VGA resolution (640x480) at 30fps. Lane detection is currently performed offline in Matlab using the captured data.

The different data capturing scenarios that were employed: i). Driving on isolated highways in the presence of light traffic, ii). Driving on metro highways in the presence of light traffic, iii). Driving on isolated highways in the presence of moderate traffic, and iv). Driving on metro highways in the presence of moderate traffic.



(a) Estimate of location of lane markers

(b) Located lane marker

Fig. 9: Successful lane marker detection

To explain the driving scenarios in more detail, an isolated highway can be described as a highway outside the city limits and that most of the illumination is provided by the headlights of the commuting vehicles. This type of controlled illumination setting can boost the contrast of the lane markers on the road as seen by the camera, which in turn helps in their detection. In contrast, a metro highway can be described as one that passes through a large town or a city where additional illumination is commonly provided by streetlights and street signs. The presence of the artificial illumination can many times act as a distraction component and in some cases, make lane detection very difficult.

To detail the various traffic situations, light traffic can be described as a condition where the number of vehicles on the road may be few to none. The host vehicle will be able to commute near the highway speed limit and the lane detection system should face minimal distraction from neighboring vehicles. On the other hand, moderate traffic can be described as a condition where there may be a reasonable number of vehicles in the vicinity. Movement is expected between these vehicles e.g. overtaking, lane changing, going fast, slowing down etc. Taking these movements into consideration, traffic will still commute at a reasonable speed. The inclusion of the neighboring vehicles can also add to the difficulty in detecting lanes.

TABLE I: Accuracy rates of the lane detection system

Highway type	Traffic type	Average Accuracy Per Minute		
		Correct	Incorrect	Misses
Isolated	Light	92.27%	6.49%	1.22%
	Moderate	92.14%	4.43%	3.45%
Metro	Light	82.41%	12.6%	4.91%
	Moderate	75.56%	20.17%	8.26%

The permutations between the type of highways and traffic conditions described above allowed to enumerate a realistic set of situations that one would encounter while driving at night. The results shown in Table I showcase the quality of the proposed lane detection system when tested on 4 hours of captured video. The metric used to test the quality of the system is accuracy per minute. This metric is chosen over a simple frame-wise approach to allow consistency in results when tested on videos with different frame rates. In Table I, the Correct column represents the percentage of correct detections per min; while, the Incorrect and Misses column represent the percentage of false positives and undetected lanes respectively.

As expected, the high contrast of the lane markers on isolated highways resulted in the high detection rates as shown in Table I. Additionally, neighboring vehicles and the illumination from their headlights appeared to have little to no effect on the average accuracy rates. Fig. 10 shows several cases of successful lane detection on an isolated highway. Unfortunately, the lane detection on metro highways had lower accuracy. The artificial illumination and visibility of neighboring vehicles and lanes acted as distractions on many occasions leading to the reduced accuracy rates. As these highways also face heavy traffic on a daily basis, the quality

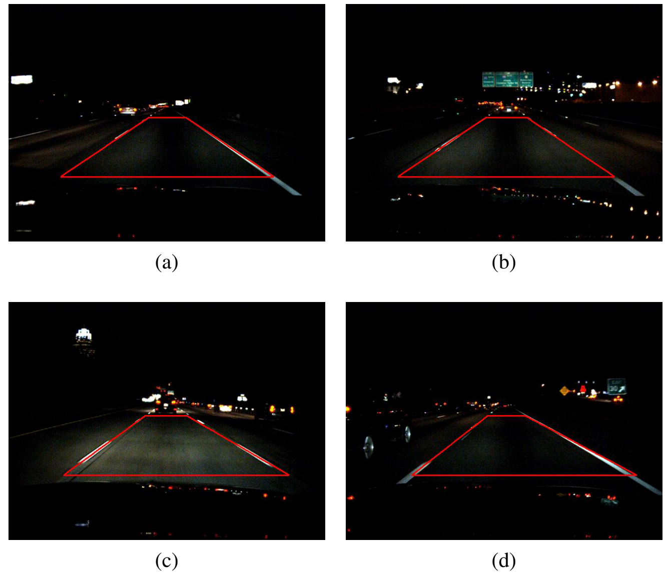


Fig. 10: Lane detection on an isolated highway. (a)-(b) detection during light traffic. (c)-(d) detection during moderate traffic.

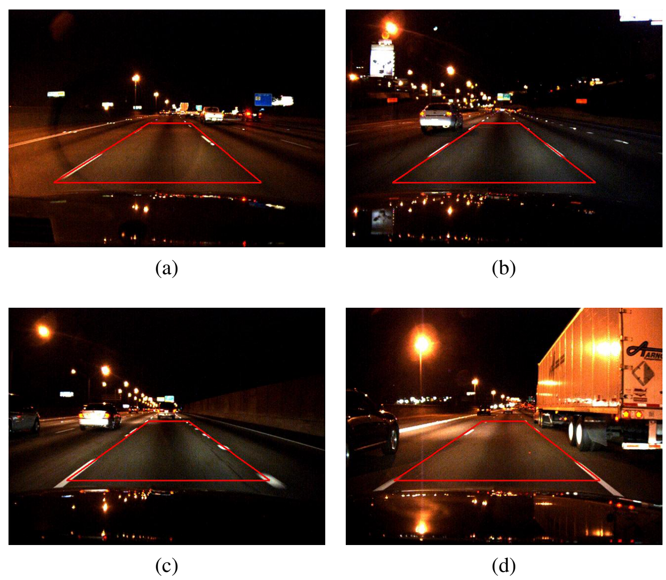
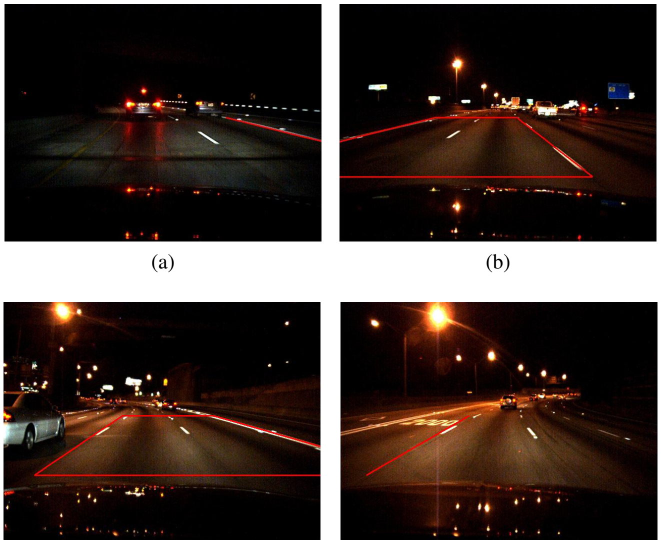


Fig. 11: Lane detection on an metro highway. (a)-(b) detection during light traffic. (c)-(d) detection during moderate traffic.

of the lane markers and concrete deteriorates over time, making detection of the required features sometimes difficult. Nonetheless, the accuracy is not low enough to be deemed unusable as accurate detections have been shown in Fig. 11.

Some cases of incomplete and missed detections are shown in Fig. 12. The age and lack of maintenance of the road results in faded lanes. Additionally, the bright illumination from the street lights can also saturate the appearance of the lane markers. The age, lack of maintenance and bright illumination are contributing factors that can sometimes make lanes impervious to detection. On rare occasions, certain portions



(a) (b) (c) (d)

Fig. 12: Few cases where the proposed system failed

of trailers and trucks are also detected as lanes due to the long and straight line features on their bodies. The presence of neighboring lanes on a multi-lane highway lead to occasional mis-detections, dropping the accuracy rates as shown in Table I.

V. Conclusions And Future Work

Presented in this paper is a layered approach towards lane detection. The features that make this approach novel are the: i) temporal blur, ii) low resolution Hough transform, and iii) iterated matched filtering. The temporal blur helps to stretch the dashed traffic lanes making them easier to detect, while the Hough transform and matched filtering helped in finding better estimates of the lane markers.

The system was tested using real-world data recorded on the highways of Atlanta, GA. The videos were captured in conditions that depicted light to moderate traffic and on highways in isolated and metro areas. The accuracy rates over 90% on isolated highways showed that the high contrast of the lane markers played a very important role in their successful detection. In metro areas, the lower accuracy rates were a result of the abundance of artificial illumination causing the reduction of contrast of the lane markers. In addition, the deterioration of the road and lane markers due to age and traffic also contributed to this effect. Additional processing will be needed to accommodate the fluctuating illumination in big city environments.

As the proposed lane detection system was targeted for night time usage, the assumptions made to optimize its operation did not hold well during the day; as a result, the proposed system faced a lot of difficulty in performing day time lane detection. Further investigation will need to be conducted to ensure accurate day time operability. In addition, the custom built tracker will be replaced in favor of proven trackers like Kalman and Particle filters.

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