

# Man Machine Interaction in Autonomous Vehicles - 02

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**Abstract:** *Today, and possibly for a long time in the near future, the complete driving task is too complex an activity to be fully formalized as a sensing-acting robotics system that can be explicitly solved using model-based and learning-based approaches in order to achieve fully unconstrained vehicle autonomy. This is especially true for unconstrained, real-time operations where the permissible range of error is extremely small and the number of limiting cases is extremely large. Until these problems are solved, human beings will remain an inevitable part of the driving task, monitoring the AI system as it performs anywhere from 0 to just under 100 percent of the driving. Overtaking and lane-changing is a critical part of vehicle automation. Though automation in automobiles has increased security and decreased environmental issues, it causes driver to be less active generating passive fatigue. This passive fatigue can lead to failure in responding quickly if needed. This led automation to keep driver active even though he/she is not required to take up full control all the time. This paper presents the need for alerting the driver during overtaking and lane-changing to avoid accidents and disastrous outcomes. The model uses image processing for lane detection and identification of obstacles, vehicles, and lane tracking. It calculates the relative velocity during overtaking and the system will share the scenarios with the driver, using alert systems. We demonstrate the capabilities and features of our system through real-world experiments using four vehicle's videos processed on the road.*

**Keywords:** Driving Assistance, Computer Vision, Object Detection, Object, Object Recognition, Object Identification, Image Segmentation, Video Segmentation, Computer Vision Representations, Image Representations, Graphics Input Device, Displays And Imager.

## I. INTRODUCTION

The idea that human beings are poor drivers is well documented in popular culture. While this idea is often overdramatized, there is some truth to it in that we're at times distracted, drowsy, drunk, drugged, and irrational decision makers. As human beings, we naturally take for granted how much intelligence, in the robotics sense of the word, is required to successfully attain enough situation awareness and understanding to navigate through a world full of predictably irrational human beings moving about in cars, on bikes, and on foot. It may be decades before most cars on the road are fully autonomous. During this time, the human is likely to remain the critical decision maker either as the driver or as the supervisor of the AI system doing the driving. Autonomous vehicles are capable of sensing environment using various techniques viz. IR and Ultrasonic rays, image processing, global positioning system, RADAR etc.

The controller is designed to gather data from all inputs and analyse it thoroughly to find the perfect path for vehicle along with obstacles. Controller should be capable of locating other cars on road travelling in same directions as well as in opposite directions with their respective speeds to avoid mishaps. Majority of the road accidents, around the world, happens because of lack of attentiveness during driving. Multi-tasking while driving, using mobile phone while driving, drunk driving, sleepiness, etc., are all cases where the driver is not attentive towards driving. Of all the accidents that happen due to lack attentiveness, a huge portion of them occur during over taking and lane changing. These two processes require complete attention and rely heavily on the driving of others on the road. An alert system, during lane changing and over taking, is an effective way of bringing the driver's attention to the action of driving. To overcome this problem, a novel but simple model is introduced that will alert the driver/drivers the driver during overtaking and lane-changing to avoid accidents and disastrous outcomes. The model uses image processing for lane detection and

identification of obstacles, vehicles, and lane tracking. It calculates the relative velocity during overtaking and the system will share the scenarios with the driver, using an alert system.

## II. ALGORITHMS

### 2.1 YOLO (YOU ONLY LOOK ONCE):

YOLO, Also Known as You Only Look Once is one of the most powerful real-time object detector algorithms. It is called that way because unlike previous object detector algorithms, like R-CNN or its upgrade Faster R-CNN it only needs the image (or video) to pass one time through its network. YOLO uses a unique neural network using the characteristics of the entire image to predict multiple boxes, each containing a specific object. To achieve this, the image is divided into 'S' x 'S' region. Then, if the center of an object is in one of these regions, the region in question is responsible for detecting the object. Each of the cells in this grid is responsible for predicting 'B' boxes all containing an object as well as a score representing the level of confidence for the object present in the box. If there are no objects in the cell, this score should be zero. Otherwise, if an object is in the cell, the score will be equal to the intersection over union (IoU) between the predicted box and the ground truth of the image. Then, we need the class-specific confidence scores for each box which is done using a convolutional neural network based on the GoogLeNet network. The output of this algorithm will be the image (or video), sent as the input, with the objects localized and the class attached to it. YOLO reasons at the level of the overall picture, rather than examining successively several regions. It is actually one of the most powerful and used object detector algorithms right now in multiple fields like autonomous vehicles, poker cheat detection, and more.

YOLO is refreshingly simple, A single convolutional network simultaneously predicts multiple bounding boxes and class probabilities for those boxes. YOLO trains on full images and directly optimizes detection performance. This unified model has several benefits over traditional methods of object detection.

First, YOLO is extremely fast. Since we frame detection as a regression problem, we don't need a complex pipeline. We simply run our neural network on a new image at test time to predict detections. Our base network runs at 45 frames per second with no batch processing on a Titan X GPU and a fast version runs at more than 150 fps. This means we can process streaming video in real-time with less than 25 milliseconds of latency. Furthermore, YOLO achieves more than twice the mean average precision of other real-time systems. Second, YOLO reasons globally about the image when 1779 making predictions. Unlike sliding window and region proposal-based techniques, YOLO sees the entire image during training and test time, so it implicitly encodes contextual information about classes as well as their appearance.

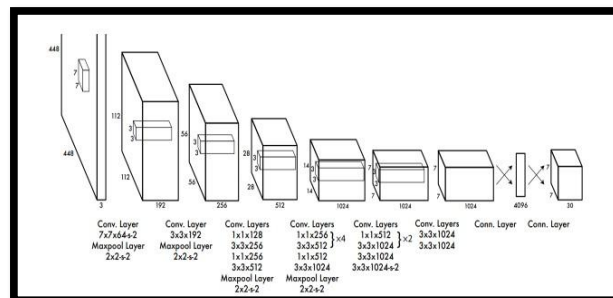


Figure 1 YOLO Architecture

### 2.1 Canny-Edge Algorithm

Canny Edge Detection is a popular edge detection algorithm. Canny edge detection is a technique to extract useful structural information from different vision objects and dramatically reduce the amount of data to be processed. It has been widely applied in various computer vision systems. Canny has found that the requirements for the application of edge detection on diverse vision systems are relatively similar. Thus, an edge detection solution to address these requirements can be implemented in a wide range of situations. Among the edge detection methods developed so far, Canny edge detection algorithm is one of the most strictly defined methods that provides good and reliable detection. Canny-Edge algorithm consists of 5 methods –

### A. Noise Reduction

Since the mathematics involved behind the scene are mainly based on derivatives (cf. Step 2: Gradient calculation), edge detection results are highly sensitive to image noise. One way to get rid of the noise on the image, is by applying Gaussian blur to smooth it. To do so, image convolution technique is applied with a Gaussian Kernel (3x3, 5x5, 7x7 etc...). The kernel size depends on the expected blurring effect. Basically, the smallest the kernel, the less visible is the blur. In our example, we will use a 5 by 5 Gaussian kernel. The equation for a Gaussian filterkernel of size  $(2k+1) \times (2k+1)$  is given by:

$$H_{ij} = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{(i-(k+1))^2 + (j-(k+1))^2}{2\sigma^2}\right); 1 \leq i, j \leq (2k+1)$$

### B. Gradient Calculation

The Gradient calculation step detects the edge intensity and direction by calculating the gradient of the image using edge detection operators. Edges correspond to a change of pixels' intensity. To detect it, the easiest way is to apply filters that highlight this intensity change in both directions: horizontal (x) and vertical (y). When the image is smoothed, the derivatives  $I_x$  and  $I_y$  with respect to x and y are calculated. It can be implemented by convolving I with Sobel kernels  $K_x$  and  $K_y$ , respectively:

$$K_x = \begin{pmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{pmatrix}, K_y = \begin{pmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{pmatrix}.$$

Figure 3 Gradient Calculation Formula

Then, the magnitude G and the slope  $\theta$  of the gradient are calculated as follow:

$$|G| = \sqrt{I_x^2 + I_y^2},$$

$$\theta(x, y) = \arctan\left(\frac{I_y}{I_x}\right)$$

Figure 4 Slope and Magnitude Calculation Formula NON-MAXIMUM SUPPRESSION –

Ideally, the final image should have thin edges. Thus, we must perform non-maximum suppression to thin out the edges. The principle is simple: the algorithm goes through all the points on the gradient intensity matrix and finds the pixels with the maximum value in the edge directions. Then non-max-suppression steps are:

1. Create a matrix initialized to 0 of the same size of the original gradient intensity matrix.
2. Identify the edge direction based on the angle value from the angle matrix.
3. Check if the pixel in the same direction has a higher intensity than the pixel that is currently processed.
4. Return the image processed with the non-max-suppression algorithm.

### C. Double Threshold

The double threshold step aims at identifying 3 kinds of pixels: strong, weak, and non-relevant:

1. Strong pixels are pixels that have an intensity so high that we are sure they contribute to the final edge.
2. Weak pixels are pixels that have an intensity value that is not enough to be considered as strong ones, but yet not small enough to be considered as non-relevant for the edge detection.
3. Other pixels are considered as non-relevant for the edge.

Now you can see what the double thresholds holds for:

1. High threshold is used to identify the strong pixels (intensity higher than the high threshold)
2. Low threshold is used to identify the non-relevant pixels (intensity lower than the low threshold)
3. All pixels having intensity between both thresholds are flagged as weak and the Hysteresis mechanism (next step) will help us identify the ones that could be considered as strong and the ones that are considered as non-relevant.

### D. Edge Tracking by Hysteresis

Based on the threshold results, the hysteresis consists of transforming weak pixels into strong ones, if and only if at least one of the pixels around the one being processed is a strong one, as described below:

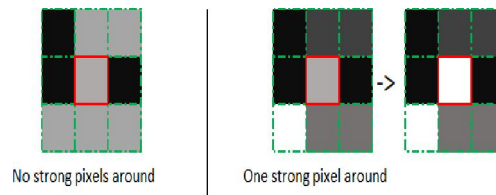


Figure 2.4 Pixel Selection in Edge Tracking by Hysteresis Diagram

### III. WORKFLOW

#### 3.1 Lane-Detection

1. The video is captured and read frame by frame.
2. Apply Canny Edge Detection to find the all the edges inthe image.
3. Find the region of interest in the image.
4. Apply Hough Transform to find straight lines
5. Find the average sloped lines on the left and right andweighted add it with the original image.

#### 3.2 Object-Detection

1. Load YOLO to load model from the disk and pass theimage through the network and obtain classification.
2. Using OpenCV, the video is captured and read frame byframe.
3. Perform Mean Subtractionand scaling usingdnn.blobFromImage()
4. Get Box Dimensions for the objects
5. Draw labels around the identified objects using Non-Maximum Suppression.

#### 3.3 Voice Alert System

1. Pre-set messages using Google Text To Speech (gTTS)API.
2. Message during lane changing.
3. Over-taking assistance message.

### IV. DATAFLOW DIAGRAM AND SYSTEMFLOW DIAGRAM

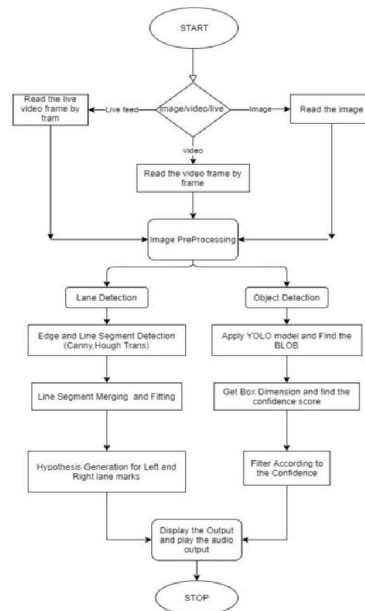


Figure 5 Dataflow Diagram

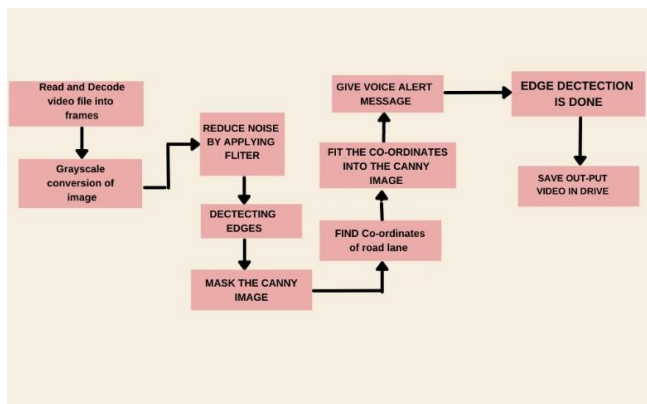


Figure 6 System Flow Diagram

### V. LIMITATIONS OF EXISTINGSYSTEMS

1. Models cannot decide over which dataset can be the best to be used.
2. Man Machine Interaction signals take much time for delivering alert messages.
3. YOLO might make some localization errors.
4. Video processor might not be able to process the video accurately.
5. Background noise during analysis of video is not avoided.

### VI. PROPOSED SYSTEM

Computer Vision and AI is helping to design models which will assist drivers in the perception of any dangerous situations before, to avoid accidents after sensing and understanding the environment around itself. To date there have been numerous studies into the recognition. Traffic accidents have become one of the most serious problems. The reason is that most accidents happen due to negligence of the driver. Rash and negligent driving could push other drivers and passengers in danger on the roads. More and more accidents can be avoided if such dangerous driving condition is detected early and warned to other drivers. Lane detection is not enough for avoiding mishaps while driving. Our proposed software model is also providing some basic alert messages when lanes are changed while driving which can be very helpful as the driver will not have to constantly look at the screen while he/she/they change the lanes. This prototype has compared various detection methodologies, data processing techniques, data storing logic, data analysis process and has come up with a software code which will give the desired output. The model makes use of COCO dataset, YOLO and Canny edge detection, Houghtransform algorithm and OpenCV python for successful implementation. At first the video is taken as an input and processed or analysed to obtain the lane detection and object detection using YOLO, Canny edge and Houghtransform algorithm. Then depending upon the changing lanes, the model yields desired voice alert messages while the detection of lanes and objects is still in process.

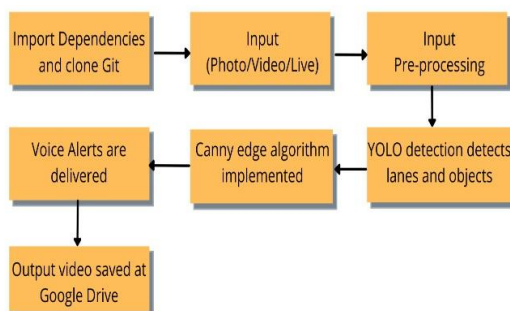


Figure 7 System Architecture.

Once the entire video is analysed, the model saves the new processed video with detected lanes and objects along with canny edge detections in the drive folder mentioned. The model is brought in use using Google Collab and OpenCV

using python programming. The proposed model will be very useful in autonomous vehicles and will help in reducing road accidents if brought into major level implementation. The below System Architecture diagram explains the working of the proposed model in a very basic way.

### **VII. ADVANTAGES**

1. Message during lane changing.
2. The system works as a bridge between the current vehicle technology which is fully manually controlled and autonomous vehicles.
3. It helps the user build trust and confidence in autonomous vehicle technology.

### **VIII. CONCLUSION**

Thus, a survey on lane and object detection and voice alerting system can prove to be helpful in avoiding road accidents and an efficient system in autonomous vehicles. This proposed model compares various factors to build a efficient model from the existing ones. This model proposed will be helpful in lane changing, will alert the driver/user through voice alerts and will be very cost efficient. With this project we try to shift the driver's role towards a supervisory control of their vehicle. This model will assist drivers/users with technologies that will enhance the driving experience with minimum to no mishaps.

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