



A Synergistic Approach of Combining both Lane and Vehicle Detection, Tracking and Localization

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Abstract

In this paper, a synergistic approach to integrated lane and vehicle tracking for driver assistance is introduced and also the Improved on the performance of both lane tracking and vehicle Tracking modules. Further, the presented approach introduces an approach to localizing and tracking other vehicles on the road with respect to lane position, which provides an information contextual relevance that neither the lane tracker nor vehicle tracker can provide by itself

Keyword: Synergistic, lane, vehicle, detection, tracking, localization.

Introduction

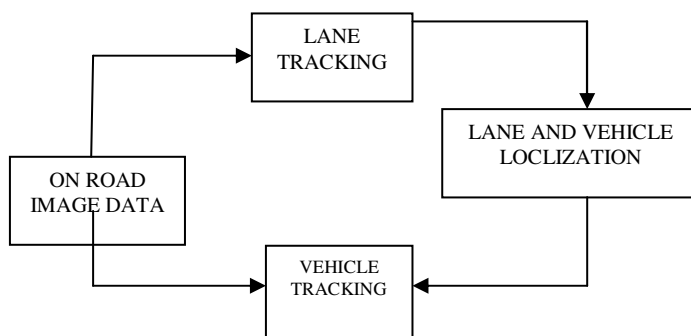
In this paper, a synergistic approach to integrated lane and vehicle tracking for driver assistance is introduced. Vehicle tracking performance has been improved by utilizing the lane tracking system to enforce geometric constraints based on the road model. This paper focus on monitoring the exterior of the vehicle. Monitoring the exterior can consist of estimating lanes¹, pedestrians, vehicles², or traffic signs and also full integration to benefit both vehicle tracking and lane tracking,

Basic Problem of the Statement

Each year, some 1.2 million people die worldwide as a result of traffic accidents. To avoid accidents focus on monitoring the vehicle exterior address one particular on-road concern. This paper adds the valuable safety functionality and provides a contextually relevant representation of the on road environment for driver assistance

Overview of the Project

Using the MATLAB code, mapping the image on road data with lane and tracking the vehicle.



Edge Detection

Edge detection¹ is the process of localizing pixel intensity transitions. The edge detection has been used by object 3 target tracking⁸, segmentation, and etc. Therefore, the edge detection is one of the most important parts of image processing.

There mainly exist several edge detection⁴ methods (Sobel, Prewitt, Roberts, and Canny). These methods have been proposed for detecting transitions in images. Early methods determined the best gradient operator to detect sharp intensity variations⁵. Commonly used method for detecting edges is to apply derivative operators on images. Derivative based approaches can be categorized into two groups, namely first and second order derivative methods. First order derivative based techniques depend on computing the gradient several directions and combining the result of each gradient. The value of the gradient magnitude and orientation is estimated using two differentiation masks⁶.

In this work, Sobel which is an edge detection method is considered. Because of the simplicity and common uses, this method is preferred by the others methods in this work. The Sobel edge detector uses two masks, one vertical and one horizontal. These masks are generally used 3x3 matrices. Especially, the matrices which have 3x3 dimensions are used in MATLAB. The masks of the Sobel edge detection are extended to 5x5 dimensions⁷, are constructed in this work. A MATLAB function, called as Sobel5x5 is developed by using these new matrices. Standard Sobel operators, for a 3x3 neighborhood, each simple central gradient estimate is vector sum of a pair of orthogonal vectors⁸. Each orthogonal vector is a directional derivative estimate multiplied by a unit vector specifying the derivative's direction. The vector sum of these simple gradient estimates amounts to a vector sum of the 8 directional derivative vectors.

a	b	c
d	e	f
g	h	i

The directional derivative estimate vector G was defined such as density difference /distance to neighbor. This vector is determined such that the direction of G will be given by the unit vector to the approximate neighbor.

Morphological Algorithm

Morph means shape. Morphological processing can solve an image processing problem, view the image processing toolbox Dilation and Erosion: Morphology is a broad set of image processing operations. The process images based on shapes⁵. Morphological operations apply a structuring element to an input image⁹, creating an output image on the same size. In a morphological operation, the value of each pixel in the output image is based on a comparison of the corresponding pixel in the input image with its neighbors. By choosing the size and shape of the neighborhood, can construct a morphological operation that is sensitive to specific shapes in the input image. The most basic morphological operations¹⁰ are dilation and erosion. Dilation adds pixels to the boundaries of objects in an image, while erosion removes pixels on object boundaries. The number of pixels added or removed from the objects in an image. Depends on the size and shape of the structuring element used to process the image. In the morphological dilation and erosion operations, the state of any given pixel in the output image is determined by applying a rule to the corresponding pixel and its neighbors in the input image.

Structuring Elements: An essential part of the dilation and erosion¹¹ operations is the structuring element used to probe the input image. A structuring element¹² is a matrix consisting of only 0's and 1's that can have any arbitrary shape and size. The pixels with values of 1 define the neighborhood. Two dimensional or flat, structuring elements are typically much smaller than the image being processed. The center pixel of the structuring element, called the origin, identifies the pixel of interest-the pixel being processed. The pixel in the structuring element containing 1's defining the neighborhood of the structuring element. The pixels are also considered in dilation or erosion processing. Three dimensional or nonflat, structuring elements use 0's and 1's to define the extent of the structuring element in the x-and y-planes and height values to define the third dimension.

Morphological Operations for Holes Filling: The formulation of the two morphology filling operation can be formulated as follow:

Hole-Pixel Initial Algorithm (HPIA)

Consider $O = \{o_0, o_1, \dots, o_k \mid o_i \text{ represents the } (x, y) \text{ pixels of object } i, k \text{ represents the number of objects in image}\}$, then the initial for this algorithm is a vector P where in (1) and (2)

$$P = \{I_i \mid i=1, 2, \dots, k\} \quad (1)$$

$$I_i = \{x_j, y_j\}, j \in \text{number of holes in object } i \quad (2)$$

This required having starting points that belongs for each hole in each object of the image, which is very difficult since the real time application for such algorithm cannot go along with this since it requires the human interaction in a very essential step which is all the latter processing depends on. However, the equation for this algorithm is in (3) taken from [1] which closes the holes of the object after certain number of epochs which means until there is no change in X_k :

$$X_k = (X_{k-1} \oplus B) \cap A, \text{ for } k = 1, 2, 3 \dots \quad (3)$$

Where X_0 is the marker with initial points I_i , B is the 3×3 SE with zeros at the corners and ones elsewhere, and A is the original input binary image.

Optical Flow

Optic flow is the pattern⁶ of apparent motion of objects, surfaces, and edges in a visual scene caused by the relative motion between an observer (an eye or a camera) and the scene. The optical flow system⁸ object estimates object velocities from one image or video frame to another. It uses either the horn-schunck or the locas- kanade method.

Optical Flow Estimation for Video: Optical flow⁹ is the distribution of the apparent velocities of objects in an image. By estimating optical flow between video frames, can measure the velocities of objects in the video. In general, moving objects that are closer to the camera will display more apparent motion than distant objects that are moving at the same speed.

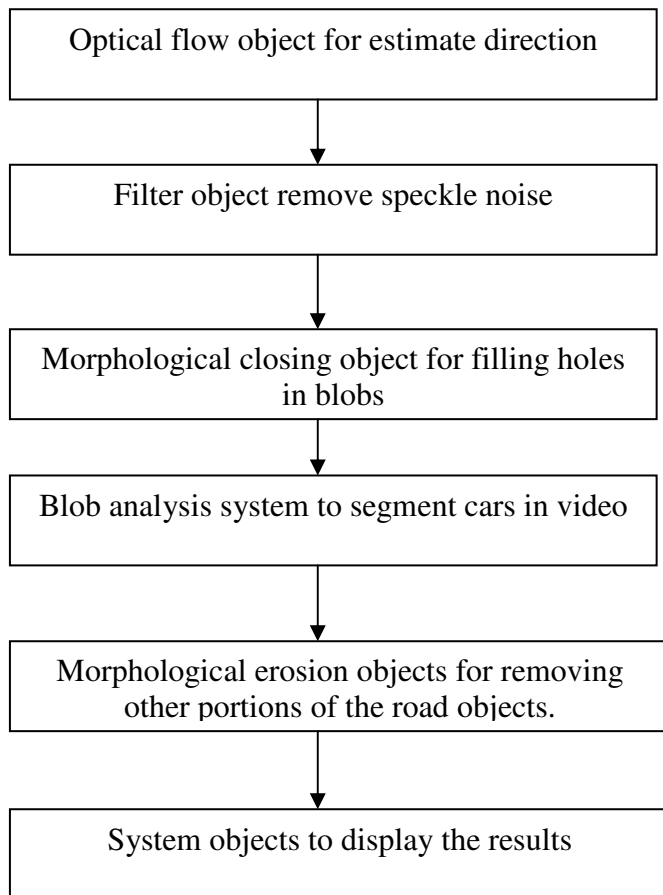
Optical flow estimation¹⁴ is used in computer vision to characterize and quantify the motion of objects in a video stream, often for motion-based object detection and tracking systems.

The model uses an optical flow estimation technique to estimate the motion vectors in each frame of the video sequence .By thresholding¹⁵ and performing morphological closing on the motion vectors, the model produces binary feature images¹³.The model locates the cars in each binary feature image⁸ using the block analysis block, then it uses the draw shapes block to draw a green rectangle around the cars.

Objects for Reading Video File: Optical flow object for estimating direction and speed of object motion. Create two objects for analyzing optical flow vectors. Filter object for removing speckle noise introduced during segmentation. Morphological closing object for filling holes in blobs.

Create a blob analysis System object to segment cars in the video. Morphological erosion objects for removing portions of the road and other unwanted objects. Create objects for drawing the bounding boxes and motion vectors.

This object will write the number of tracked cars in the output image. Create System objects to display the original video, motion vector video, the threshold video and the final result.



Firgue-1
Working Flow Chart

Simulation Results



Figure-2
Original video

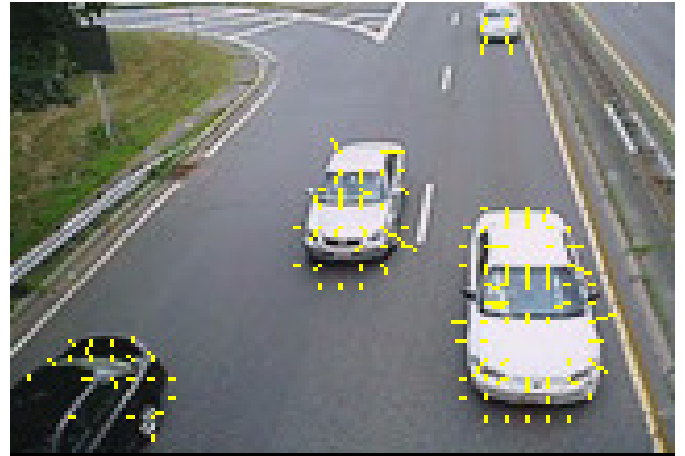


Figure-3
Motion vector



Figure-4
Threshold video

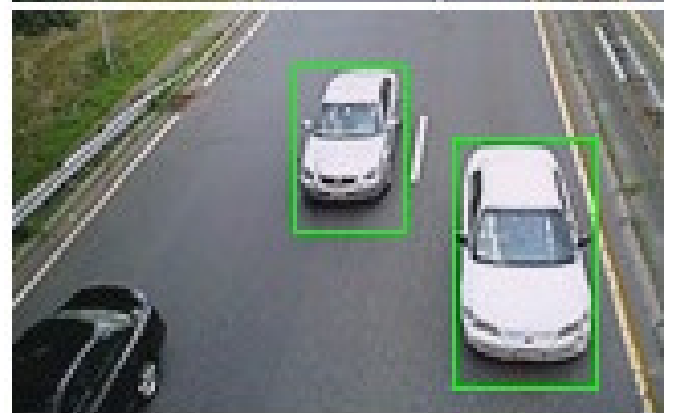


Figure-5
vehicle detection

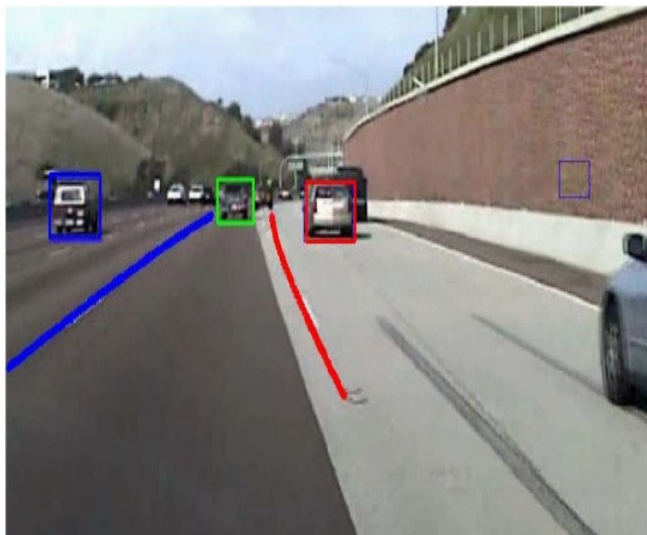


Figure-6
with respect to lane vehicle detection

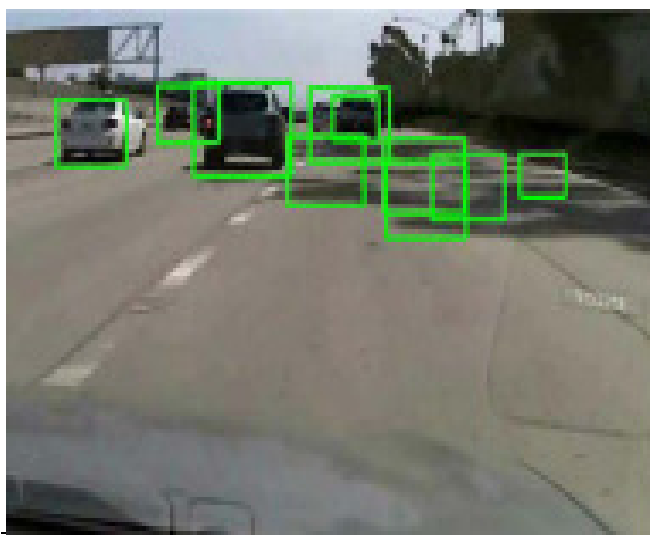


Figure-7
Localizing and tracking other vehicle on the road

Conclusion

First improved the performance of the lane tracking system, and extended its robustness to high-density traffic scenarios. Second, improved the precision of the vehicle tracking system, by enforcing geometric constraints on detected objects, derived from the estimated ground plane. Third introduced an approach to localizing and tracking other vehicles on the road with respect to the estimated lanes.

Future Work: The future work is improved version of both lane and vehicle tracking system. Next it has determined improving version of localizing and tracking other vehicle on the road with respect to lane position.

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