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Moving Object Tracking using Inverse Perspective Mapping and Optical Flow

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ABSTRACT

As objects moving at a pace create difficulty in identification so is the problem persisting in the moving vehicle recognition and tracking using passive vision sensor. This proposed tracking system is based on a camera mounted in a moving vehicle used to capture images to track another moving one. It considers tracking vehicles in open roads and highways. Inverse perspective mapping is adopted to extract a bird eye view of the road to subtract the standpoint results from the image. The image is then cropped and processed to extract the vehicle segment. The cropped image is returned to the camera view where the optical flow is utilized to estimate the vehicle direction and relative velocity based on the object's centroid displacement. The algorithm is tested on standard datasets as well as a new dataset created in Egypt's open roads. The results show robust tracking even with curved roads and fast computation which allow real-time processing even on embedded systems with low-computing resources.

Key words : Object identification, tracking, image processing, object mapping, vehicle detection.

1. INTRODUCTION

It's been long time In 1980s, when the initiation of the actually autonomous car were designed. In 1984, with the Carnegie Mellon University's Navlab, the ALV projects. A concrete advancement was made possible after couple of years in 1987, with Eureka Prometheus Project established by Mercedes-Benz and the University of Munich, Germany [20]. Since then, the working prototype autonomous vehicles have been developed by the numerous major companies like Nissan, Toyota, Audi, Volvo and research organizations.
According to official classification established in the USA by the National Highway Traffic Safety Administration, the vehicles may be classified into 5 autonomy levels [21]:

Level 0: All the time the vehicle is controlled completely by the driver
Level 1: Vehicle is automated by an individual control, using the technique of automatic braking which is really significant either the electronic steadiness and control.
Level 2: At the same time, the vehicle can be automated by two controls, which provide performance gain in adaptive cruise control along with the arrangement of lane tracking.
Level 3: All safety-critical functions are to be controlled without intervention of human's input also it gives to the driver the sufficiently comfortable transition time to retake the control of the car if it senses any condition that needs the driver to take action.
Level 4: For the entire trip, all the safety-critical functions are performed by the vehicle and it is not controlled by the driver for the given time period. This could enhance cars without drivers.

Driver assistance system is a step toward full autonomous vehicle, since all devices or algorithms created for DAS may be adapted for autonomous systems. The two main issues for any of the advanced driver assistance system are: First, the real time performance and second, the robustness against several environment conditions [22], [34].
Systems that rely on vision [31], [36], [37] are becoming more popular and widely used as a part of enhancing driver security and providing alerts when required to the driver if any obstacles is likely to come forward. However, understanding the road environment using artificial vision system is a challenging task. The road environment is the one of the most complex scenarios as it is extremely variable due to change in illumination conditions, change in weather conditions. The background of the road is cluttered and changing rapidly. The road environment is completely uncontrolled dynamic outdoor environment.
As this research work, proposes a automation system to identify and track the vehicles also to estimate their speed using only a one camera system installed in a stirring vehicle.
In this research paper we have tried to portray things as follows: the next sub-section represents the literature analysis. The following section describes all proposed system used to accomplish the vehicle identification, the tracking process along with the velocity estimation of the vehicles. The upcoming section after this introduces the outcomes of the projected system tested using a standard dataset and on our own test cases. Finally, the fifth section provides the decision and a forthcoming work to the presented work.

2. LITERATURE REVIEW

Inverse perspective mapping IPM were used in [1], [2] to segment the road image into classes for region of interest, vehicles and background. First a prior handling stage was executed, in this the image quality was investigated and if the quality was low it was enhanced. Then this modified or enhanced quality image was hosted into the warping module that is then transformed the image from the image domain to the world domain. The pixels of the image are labeled with the segmentation module into three categories. Finally, the positions and measurements of the vehicles in the images were estimated using the object detection and the tracking module.

Recent work for lane detection is based on IPM [25], [27], [28], [29] and particle filters [26]. The IPM is functional in the preprocessing period to enhance the completion of the algorithm. Where it eradicates the perspective consequence inside the unprecedented image such that lane patterns appear to be vertical and parallel.

Obstacle and vehicle detection [3], [23] is done the same way, where a dissimilarity image in which the best square hindrances were distorted into two triangles that can be produced by the stereo IPM technique. The barrier exposure process was designed on the existence of the couples of these triangles.

Rahim et al. [4] emphasized on identifying the velocity of vehicle which was moving and attempted to deploy stationary camera and traffic monitoring applications. First, the current frame was subtracted with the reference frame. The subsequent images were categorized by presenting repetitive erosion, dilation along then image is filled so eradicate any dumps in the object. center of each thing was processed and tracked. Finally, to estimate the velocity, the transformation between the center at time t and t-1 was computed and distributed by the edge rate. Velocity was calculated in pixels/second then converted to Km/h. similar work was proposed in [11] and [5]. However, in [5] convex hull was used to approximate the contour of the vehicle and finally, to estimate the speed of the vehicles, some geometric analyses were performed. Temiz et al. [6] used the rectification of the video frames to eliminate the perspective effect and then they used the optical flow [8] to estimate the vehicle speed, which is close to [24]. In [13] vehicle path estimated using accumulated ROI based on 3D wavelet transform.

Yik [7] proposed a system that is based on Capturing information regarding the object of interest, this required the author to filter the right scene from the captured data frame sets and then applying the correct corresponding filters which are median filters. The data was acquired using the digital cameras. Then, estimating the position of individual vehicles using A forge net library, estimating where the actual vehicle is located using search in the projected area and finally, calculating the velocity of movement of vehicle.

A concise review on high way traffic surveillance control based on the image processing has been presented in [9]. Several approaches have been addressed in this paper, such as area-based tracking, outline tracking, 3D model-based tracing, feature extraction-based tracing and color and pattern-based tracing [38].

Ponsa et al. [10] achieved a abridged managing time and a high correctness because of the arrangement of the vehicle recognition with the lane colorations estimation. The authors in [12] used a combined motion-based and appearance-based vehicle detection. In [14], [15], [39] a system was proposed for vehicle recognition and pursuing using several lanes built on a monocular camera. A comprehensive Kalman filter based method was used to estimation the medium trajectories.

3. PROPOSED SYSTEM

3.1 Image Acquisition and Preprocessing

This research emphasizes on the vehicle tracking using a camera attached inside a stirring vehicle. the captured video frames are converted to grayscale and cropped to reduce the complexity of the images and to focus on the street situation, as shown in Figure 1. The surroundings for the image are cropped and the required site for tracking the vehicle is in place which reduceses the time for processing the image under investigation this is important process to speed up processing of the image under identification.

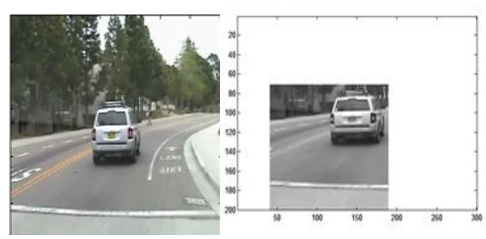

Figure 1: The original Image and the Image after preprocessing

3.2 Road Lane Extraction

Road lane extraction is a main step and very necessary for the simplification and robustness of the following steps for vehicle detection [30] [31][32] [36]. In this work the road boarders are first extracted using local (adaptive) thresholding tracked by Canny edge detector and the Hough convert. The road way markers are then extracted by the help of global thresholding on the ROI, which represents the road region in this case. Figure 2 displays an model of an open road along the road region of interest (ROI).

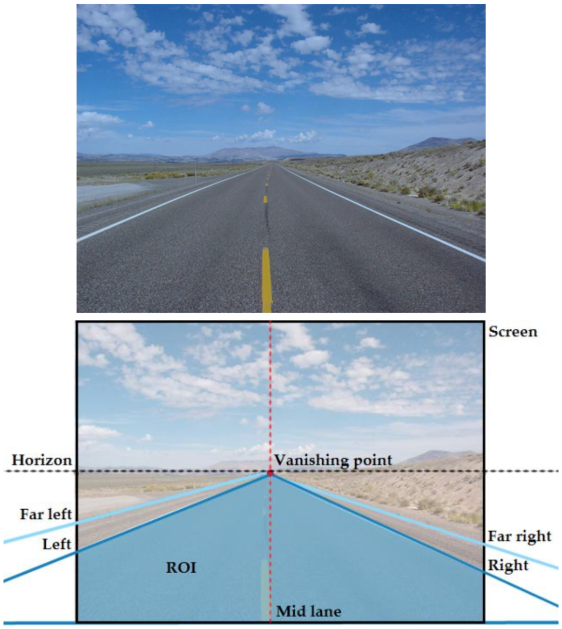

Figure 2: The input Image along the road region

The input colored image is converted to grayscale and cropped as introduced in the preprocessing, then it is binarized by a local thresholding. Afterwards it has been subject to the Canny edge detector [37] and the Hough transform [33][35] as displayed in Figure 3.

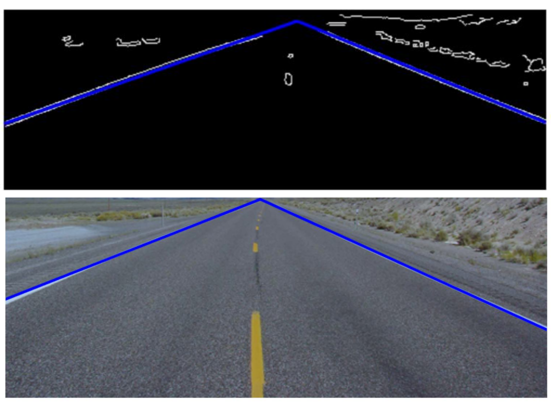

Figure 3: Extracting the road region of interest.

This ROI are then processed simply by means of a global thresholding to extract the road lane markers as displayed in Figure 4.

Figure 4: Extracting the road track indicators using global thresholding.

3.3 Inverse Perspective Mapping

The inverse perspective mapping's main objective is to place and remap every-pixel concerning a diverse position, to produce an original two-dimensional array of pixels and to facilitate this task of the vehicle detection and the road modeling [2], [17], [18]. This technique provides a upper view image, as shown in the Figure 5. It is an upper view of the road area in visible of the vehicle, as it has been observed from a certain elevation, which removes the perspective distortion allowing some elements to be simplified, as for example:

Lane markings will appear to have the same width and they will be parallel in the IPM images.
The comparative swiftness and the distance of the object appear to be up to the scale with the real object on the road.
Using this method, the complexity of the processing is considerably reduced because of the linear relation between the space and the swiftness of the vehicle with real magnitudes, but a flat road must be assumed.

Figure 5: Bird Eye View Images

3.3 Labeling

The labeling process is used to provide a fast way of separation of the elements. But first to simplify the process, the IPM image is cropped without any change in the size and the dimension of the image. Here the right corner is where the object is identified as object of interest as shown in Figure 6.

Figure 6: Cropped IPM Image.

Using multi-thresholding technique, the different regions in the image are labeled. White pixel used for the lane markings, "vibrant gray pixels" used to identify area of the road and finally, the "opaque gray pixels" used for the occurrence of the vehicles inside scene or mainly the shade displayed on the road. Any "black pixels" were those that do not belong to any of the three previous regions and they are considered as out of interest for the following computing steps, as shown in Figure 7.

Figure 7: Labeled image

The region of the vehicle is then extracted in a twofold image as shown in Figure 8.

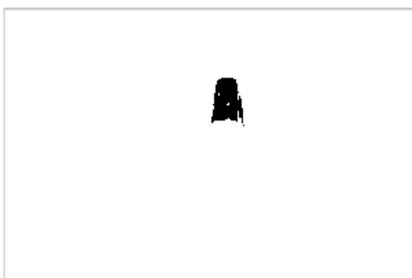

Figure 8: Binary image

3.4 Enhancement

In this stage, the binary image is inverted and processed using morphological operations to enhance the extracted region of interest (ROI). If the image shows multiple objects, the in this step the objects will be separated from each other and identified individually. Figure 9 shows the ROI extracted after the enhancement step.

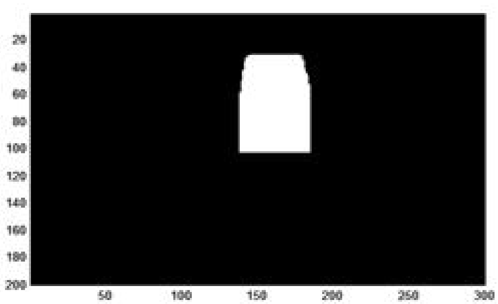

Figure 9: The ROI after enhancement.

3.5 Perspective Mapping

The perspective mapping is used to return the image to the original view from the bird's eye view [2][17][18].

There are two main objectives of the perspective mapping:

The Final outcome obtained in the non-perspective area are refined.

It augments a elevation to the vehicles detected.

When the image is back returned into the image domain, the restored region is only part of the vehicle. Therefore, the transformed binary image into the camera domain is further enhanced by applying more morphological operations. This step result on making the middle of the vehicle at the middle of the image. This step is described in Figure 10, and Figure 11.

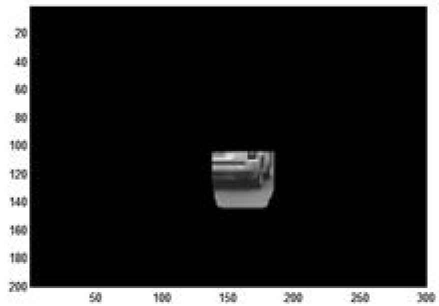

Figure 10: The image after perspective mapping and before the enhancement.

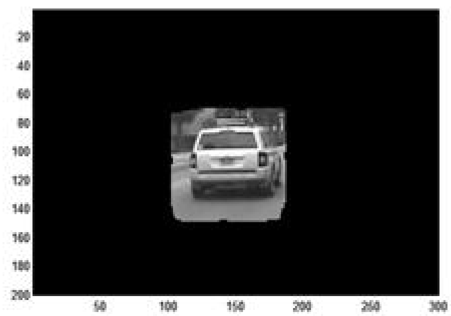

Figure 11: Car detected in image domain

3.6 Optical Flow

The method showed in this work uses two consecutive image frames to that help in calculation of motion which are located between the 2 frames that have been identified at times t and $t+\Delta t$. In general, while getting closer to the camera, the moving objects will be displayed with more apparent motion than the objects less closely that are moving with the same speed.

The optical flow utilizes the the partial derivatives along with spatial and temporal coordinates. Let us accept that the center pixel is $I(x, y, t)$ in a m x n locality and moves by Δx, Δy in the time Δt to $I(x+\Delta x, y+\Delta y, t+\Delta t)$. Since $I(x, y, t)$ and $I(x+\Delta x, y+\Delta y, t+\Delta t)$ are the images of the same point, then we have:

$$I(x, y, t) = I(x+\Delta x, y+\Delta y, t+\Delta t)$$

Supposing the association to be very small:

$$I(x+\Delta x, y+\Delta y, t+\Delta t)= I(x, y, t)+[\ \frac{\partial I}{\partial x}\Delta x + \frac{\partial I}{\partial y}\Delta y + \frac{\partial I}{\partial t}\Delta t + \dots$$

We can assume in this equation that:

$$\frac{\partial I}{\partial x}\Delta x + \frac{\partial I}{\partial y}\Delta y + \frac{\partial I}{\partial t}\Delta t = 0$$

Or

$$\frac{\partial I}{\partial x}\frac{\Delta x}{\Delta t}+\frac{\partial I}{\partial y}\frac{\Delta y}{\Delta t}+\frac{\partial I}{\partial t}\frac{\Delta t}{\Delta t}=0$$

This means the result that:

$$\frac{\partial I}{\partial x}Vx+\frac{\partial I}{\partial y}Vy+\frac{\partial I}{\partial t}=0$$

Where *Vx*, *Vy*are the velocities in the *x* and *y* modules or the visual flow of *I(x, y, t).*

Thus it could be written also in this way:

$$IxVx+IyVy=-It$$

Where *Ix*, *Iy* and *Iz* are the intensity derivative respectively in *x*, *y* and *t*. Figure 12 displays the velocity distribution in input image.

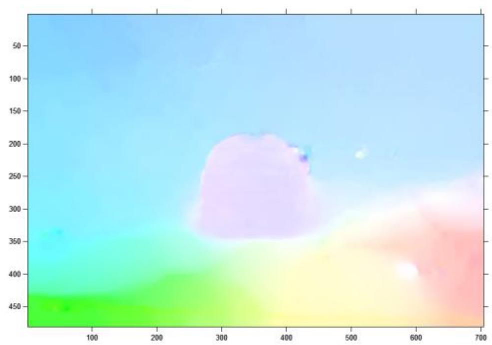

Figure 12: Velocity Distribution

4. RESULT AND DISCUSSION

The vehicle tracking process will be discussed is this section. The processing was carried out at 2.30 GHz, with 8.00 GB RAM memory in a core i5 processor. Three datasets are used to test the proposing algorithm. The first and third datasets are in [19]. The first dataset is a standard dataset that consists of a vehicle, trees, buildings and people crossing the road and the vehicle was turning right then moving forward. A sample of these dataset is shown in Figure 13. The frame rate is 30 frames/second and has frame resolution of 480 x 704 pixels. The dataset has no ground truth for vehicles trajectories therefore; it was not possible to compute statistical measures such as the absolute trajectory error and the relative trajectory error.

Figure 13: A sample of first test dataset.

All the steps of the algorithm are applied on these images. In many frames the followed vehicle appear very close the tracking camera, and hence its size appear large. Therefore, the structure used in the morphological step was chosen to be in the range of [15X15]. The tracking results of the dataset 1 are shown in Figure 14.

For every frame, the centroid of the detected moving vehicle is used to save the object's position and hence the position history of vehicle. The optical flow technique applied to estimate velocities of vehicle in x and y directions using every two consecutive image frames. To estimate the vehicle motion direction, the position and velocity information is transformed to the polar coordinate system. Where it is easy to compute the angle of the vehicle with the horizontal axis and hence to predict the direction of the movement.
The estimated trajectory in which moving vehicle shows association in opposite route of the real motion. Since the motion direction is estimated based on the difference in motion in the successive frames.
Each time the position of the vehicle is estimated a new point is added to the plot. The plot shows some errors during the detection of the vehicle and the tracking process because of the people that were crossing the street as they were detected too

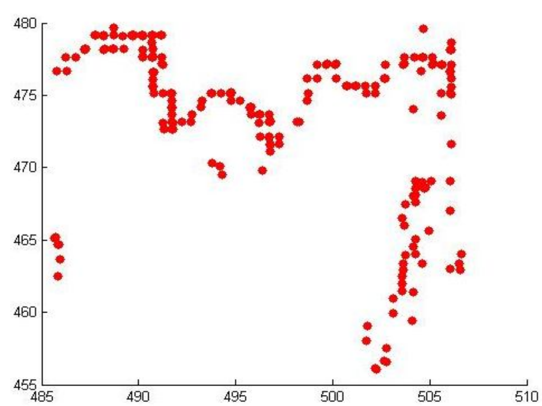

Figure 14. Vehicle Tracking for Dataset 1

The second test dataset is another standard dataset but containing a dense number of vehicles, trees, buildings and people. A sample of these data is shown in Figure 15. The challenge of using this dataset is how to track specific vehicle out of multiple ones.

Figure 15: Sample frame of the dense dataset

The same processes applied to the first test dataset are done on this dataset. The changes are only in the morphological operation steps. The size of structure element used here ranges only from [3 3] to [7 7].

The third dataset is recorded in Cairo to El-Ein-El-Sokhna Highway. It has a frame rate of 29 frames/second and is obtained with a resolution of 288 x 352 pixels. A ample dataset is displayed in Figure 16.

Figure 16: A section of the third test dataset

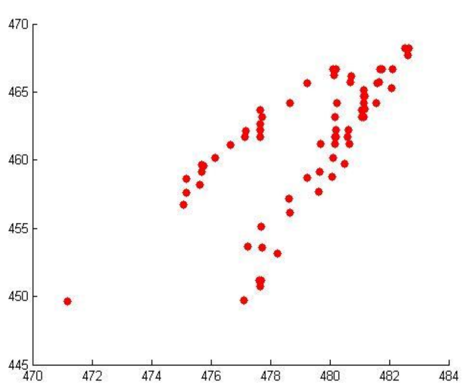

Figure 17: Vehicle Tracking for the third dataset

The images show two vehicles on the highway in a challenging conditions. The left vehicle is the target vehicle by the tracking. It is moving forward while making a little turning left and at some point the car is making a bigger rotation to the left direction.
The results if this dataset is shown in Figure 17. As expected the motion in the plotted figure is on the opposite direction as the real motion of the tracked vehicle.

5. CONCLUSION AND FUTURE WORK

The study presented explains the image processing and the computer vision system in a forward-facing monocular camera installed in a moving vehicle. Several tasks as vehicle tracking, the speed measurement and the vehicle detection are considered. Approved methods and algorithms are used to detect the vehicle location using the inverse perspective mapping based on its black shadow casted on the road, to label the objects, to enhance the segmentation of the result, to approximation the velocity of the vehicle using optical flow method and to track the displacement using the object's centroid. The success of this algorithm is that it could be used to detect the pedestrians and the other objects.

For an autonomous car several techniques must be used such as the sensors, the radar, the GPS, and the image processing because if any of these techniques fails, there should be an alternative technique doing the same work to prevent the vehicle from any accident. Finally, the algorithm used in this work has proved a good performance, efficiency and robustness for the situations.

Many open challenges are there for future research. The future research should address the problems of accurate detection when the road is crowded and with very complex situations (i.e., shadows, different weather conditions and buildings). A classifier of active traffic objects may be integrated with the tracking system to avoid tracking pedestrians passing or crossing the road while detecting the vehicle. For better system performance, more tracking conditions could be considered using the advantage of optical flow and generated motion vectors to remap pixels in IPM. Additionally, these motion vectors can be used to eliminate the problem of opposite direction tracking. Also, more tracking scenarios can be handled by extending the labeling process to consider multi-vehicle tracking.

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REFERENCES

1. Mujika, Andoni, et al. **Web-based Video-Assisted Point Cloud Annotation for ADAS validation**, *The 24th International Conference on 3D Web Technology*. ACM, pp. 1-9, 2019.
2. Arróspide, Jon, Luis Salgado, and Marcos Nieto. **Video analysis-based vehicle detection and tracking using an MCMC sampling framework,** *EURASIP Journal on Advances in Signal Processing* 2012.1 (2012). https://doi.org/10.1145/3329714.3338128
3. Massimo Bertozzi and Alberto Broggi, **GOLD: A Parallel Real-Time Stereo Vision System for Generic Obstacle and Lane Detection**, *IEEE Transactions of image processing*, 1998. https://doi.org/10.1109/83.650851
4. H. A. Rahim, U. U. Sheikh, R.B. Ahmad and A. S. M. Zain, "**Vehicle Velocity Estimation for Traffic Surveillance System**" World Academy of Science, Engineering and Technology, Vol:42010-09-22, 2010.
5. Ammar Awni Abbas, "**Estimating vehicle speed using image processing**", University of Baghdad, Al-Mansour Journal/No.14/Special Issue/(Part Two) 2010.
6. M.S. Temiz, S. Kulur, S. Dogan, **Real Time Speed Estimation From Monocular Video**, *Istanbul Technical University, Dept. of Geomatics Engineering, Istanbul, Turkey*, 25 August - 01 September 2012.
7. Chan Chia Yik, **Vehicle tracking and speed estimation system**, *Faculty of Computer System & Software Engineering, University Malaysia Pahang*, June 2012.
8. C. Liu., **Beyond Pixels: Exploring New Representations and Applications for Motion Analysis**, Doctoral Thesis. Massachusetts Institute of Technology. May 2009.
9. Raad Ahmed Hadi, Ghazali Sulong and Loay Edwar George, "**Vehicle Detection and Tracking Techniques: A Concise Review**", *Department of Computer Science, University Technology Malaysia, Skudai, Malaysia, Signal & Image Processing: An International Journal (SIPIJ)* Vol5, No.1, February 2014. https://doi.org/10.5121/sipij.2014.5101
10. Daniel Ponsa, Joan Serrat and Antonio M. López, **On-board image-based vehicle detection and tracking**, *Computer Vision Center and Computer Science Department, Barcelona, Spain*, pp. 783-805, (2011).
11. Shweta Joshi, **Vehicle Speed Determination Using Image Processing**, *Department of Electronics & Telecommunication Engineering, Rajarambapu Institute of Technology*, Rajaramnagar, Islampur, Maharashtra, India, April 2014.
12. Alfredo Ramirez, EshedOhn-Bar and Mohan M. Trivedi, **Go with the flow: Improving Multi-View Vehicle Detection with Motion Cues**, *Laboratory for Intelligent and Safe Automobiles, University of California San Diego*, La Jolla, CA, 92092 USA, *IEEE international Conference on Pattern Recognition* 2014. https://doi.org/10.1109/ICPR.2014.709
13. Salem, M.A.-M., Appel, M., Winkler, F., Meffert, B. **FPGA-based smart camera for 3D wavelet-based image segmentation**, *2nd ACM/IEEE International Conference on Distributed Smart Cameras, ICDSC* 2008.
14. Kristian Kovačić, Edouard Ivanjko and Hrvofe Gold, **Real Time Vehicle Trajectory Estimation on Multiple Lanes**, *Department of Intelligent Transportation Systems, Faculty of Transport and Traffic Sceinces, University of Zagreb*, Croatia, 2014.
15. Al-Berry, M. N., Salem, M. A.-M., Hussein, A.S., Tolba, M. F. **Spatio-temporal motion detection for intelligent surveillance applications**. *International Journal of Computational Methods*, Vol.12 (1), 2015. https://doi.org/10.1142/S0219876213500977
16. Getting Started with MATLAB® 7 The dataset used in this work was imported from the internet in April 15, 2015"http://cvrr.ucsd.edu/LISA/vehicledetection.html".
17. Sovira Tan, Jason Dale, Andrew Anderson, Alan Johnston, **Inverse perspective mapping and optic flow: A calibration method and a quantitative analysis**, *Image and Vision Computing*, Vol. 24, Pages 153-165, 2006.
18. Miguel Oliveira, Vitor Santos, Angel D. Sappa, **Multimodal inverse perspective mapping, Information Fusion**, pp.108.121, Vol 24, July 2015.
19. Sayanan Sivaraman and Mohan M. Trivedi, **A General Active Learning Framework for On-road Vehicle Recognition and Tracking,** *IEEE Transactions on Intelligent Transportation Systems*, 2010. https://doi.org/10.1109/TITS.2010.2040177
20. Xie, Ming, Laurent Trassoudaine, Joseph Alizon, Monique Thonnat, and Jean Gallice.Active and **intelligent sensing of road obstacles: Application to the European Eureka-PROMETHEUS project**. *(4th) IEEE International Conference on Computer Vision*, pp. 616-623, 1993.
21. **SAE Levels of Driving Automation. The Center for Internet and Society at Stanford Law School** [On-line] Available: http://cyberlaw.stanford.edu/loda [2019, Oct. 15]
22. Janai J, Güney F, Behl A, Geiger A, **Computer vision for autonomous vehicles: Problems, datasets and state-of-the-art,** (2017).
23. Salem, M.A.-M., Almotairi, S. **Vehicle detection in remote sensing images**. *International Journal of Innovative Technology and Exploring Engineering*, Vol 8 (11), pp. 928-933, 2019.
24. S. Indu, Manjari Gupta and Prof. Asok Bhattacharyya, **Vehicle Tracking and Speed Estimation using Optical Flow Method**, *ECE Department, Delhi Technological University*, Bawana Road, Delhi,110042, Jan 2011.
25. Zu Whan Kim. **Robust lane detection and tracking in challenging scenarios**. *IEEE Transactions on Intelligent Transportation Systems, 9(1)*:1626, March 2008.

26. Christopher Sherlock Lisa Turner. **An introduction to particle filtering**. May 2013.
27. D. Seo and K. Jo, **Inverse Perspective Mapping based road curvature estimation**, 2014 *IEEE/SICE International Symposium on System Integration, Tokyo*, pp. 480-483, 2014. https://doi.org/10.1109/SII.2014.7028086
28. N.T, Vighnesh & Anil, Rachana & D, Rohith & Sharvana, Sanjana & Hegde, Rajeshwari & Nagabhushana, B, **Application of Inverse Perspective Mapping for Advanced Driver Assistance Systems in Automotive Embedded Systems**. *International Journal of Reconfigurable and Embedded Systems (IJRES)*, 2018.
29. Wang, Qidong & Wei, Zhenya & Wang, Jiaen & Chen, Wuwei & Wang, Naihan, **Curve recognition algorithm based on edge point curvature voting. Proceedings of the Institution of Mechanical Engineers, Part D**: *Journal of Automobile Engineering*. 2019.
30. Salem, M.A.-M., Klaus, K., Winkler, F., Meffert, B. **Resolution mosaic-based smart camera for video surveillance**, *3rd ACM/IEEE International Conference on Distributed Smart Cameras*, ICDSC 2009 https://doi.org/10.1109/ICDSC.2009.5289364
31. Al-Berry, M.N., Salem, M.A.-M., Hussein, A.S., Tolba, M.F., **Spatio-temporal motion detection for intelligent surveillance applications**, *International Journal of Computational Methods*, 2015.
32. Salem, M.A.-M**., On the selection of the proper wavelet for moving object detection**, *Proceedings* **-** *ICCES'2011: 2011 International Conference on Computer Engineering and Systems*, pp. 207-212, 2011.
33. Mingfa Li , Yuanyuan Li , and Min Jiang, Lane **Detection Based on Connection of Various Feature Extraction Methods**, *Advances in Multimedia Volume*, pp. 13, 2018.
34. Salem, M.A.-M. **Multi-stage localization given topological map for autonomous robots**, *Proceedings* **-** *ICCES 2012: International Conference on Computer Engineering and Systems*, pp. 55-60, 2012.
35. Shalaby, M.M., Salem, M.A.-M., Khamis, A., Melgani, F., **Geometric model for vision-based door detection**. *Proceedings of 2014 9th IEEE International Conference on Computer Engineering and Systems*, pp. 41-46, 2014 https://doi.org/10.1109/ICCES.2014.7030925
36. Chen, Wenxiang, Yingna Li and Chuan Li. **A Visual Detection Method for Foreign Objects in Power Lines Based on Mask R-CNN,** *International Journal of Ambient Computing and Intelligence (IJACI)*, (2020)
37. Yang, Xiaojun and Xiaoliang Jiang. **A Hybrid Active Contour Model based on New Edge-Stop Functions for Image Segmentation**, *International Journal of Ambient Computing and Intelligence (IJACI)*, (2020) https://doi.org/10.4018/IJACI.2020010105
38. Dey, N., Ashour, A. S., & Hassanien, A. E. **Feature detectors and descriptors generations with numerous images and video applications: a recap**. *In Feature Detectors and Motion Detection in Video Processing IGI Global*, pp. 36-65, 2017.
39. Al Berry, M. N.; Salem, M. A.-M. Ebeid, H. M.; Hussein, A. S.; Tolba, M. F., **Action recognition using stationary wavelet-based motion images**, *Advances in Intelligent Systems and Computing*, Vol 323, , pp.11, 2015. https://doi.org/10.1007/978-3-319-11310-4_65