Vision Based Obstacle Detection and Avoidance for Autonomous Vehicles

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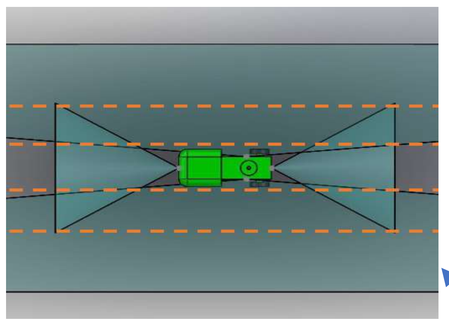
ABSTRACT

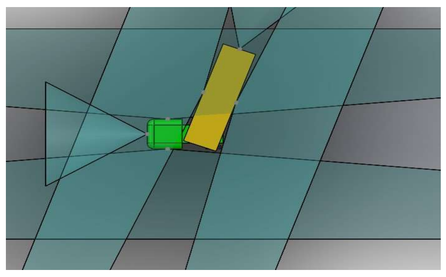
In this project, it is aimed to design a 360-degree obstacle detection and avoidance system using the data obtained from cameras located on autonomous heavy vehicles such as trailer trucks, straight-body trucks and lorries. To use as few number of cameras as possible, in addition to perspective cameras large field of view fish eye cameras are also utilized. State of the art object detection and classification algorithms are used to detect the obstacles around the vehicle using captured images and classify the objects in real time. To quantify detection and classification performance in realistic scenarios, algorithms are implemented in Truck Maker Simulation environment.

INTRODUCTION

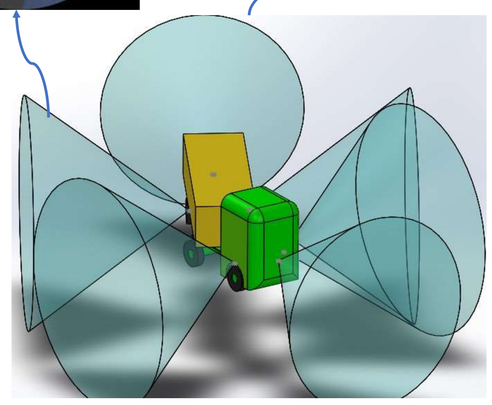
- Autonomous vehicles are becoming very popular all around the world due to several advantages including safety, fuel efficiency and travel time reduction [1].
- Some companies including Otto, Volvo, Daimler and Peterbild already announced that self driving trucks will be available in 5 to 10 years [2].
- Towards truly autonomous vehicles Advanced Driver-Assistance Systems (ADAS) is an important step. ADAS utilizes various sensors such as radar, LIDAR and cameras.
- Envrionment perception is critical and the role of vision in this process is very important.
- In this project, a 360-degree obstacle detection and avoidance system based on multiple cameras is designed and developed for autonomous trucks.
- Perspective and fisheye cameras are used to capture images of the surroundings of the trucks.
- State of the art automatic stitching, automatic rectification, object detection and classification algorithms are used for obstacle detection and avoidance.
- Algorithms should operate in real-time, and they should be fast and accurate due to traffic conditions.
- Full coverage of the scene should be obtained by using as few sensors as possible due to the relatively bigger sizes of the trucks .



Top View of Truck Camera System



Top View of Trailer-Truck Camera System



Multiple Camera System Design

Truck Maker Simulation

METHODOLOGY AND RESULTS

Distortion Rectification

- Distorted fisheye images decrease accuracy of the detection algorithms. Therefore, distorted images should be rectified for proper image stitching.
- Distortion can be modeled as a polynomial function approximated from Taylor series expansion [3].
- Edge detection and polygonal approximation are used in the estimation of the distortion parameters [4].
- Parameters are estimated by minimizing the total distortion error.

Distorted Fisheye Image

Rectified Fisheye Image

SSD Detection Performance

	Before Rectification	After Rectification
FPS	4.86	3.93
Accuracy	48.1%	70.67%

Performance Results Before & After Rectification

Image Stitching

Feature Matching | **Image Registration** | **Bundle Adjustment**

- Situational awareness of the driver can be increased with providing a 360-degree image around the truck.
- Views from multiple camera system are stitched automatically with Feature Matching, Image Registration and Bundle Adjustment steps [5].

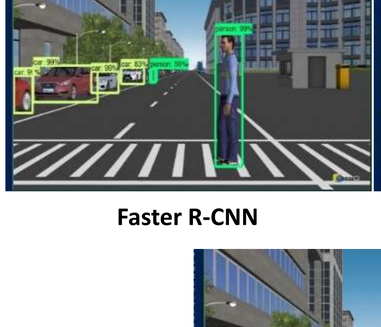
Images to be Stitched

Panoramic Image Generated by Image Stitching

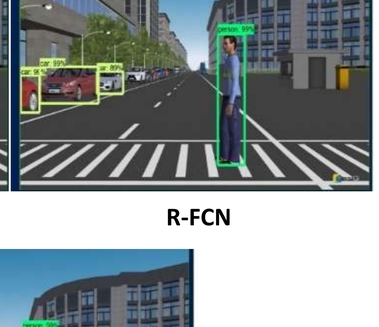
Object Detection & Classification

Faster R-CNN | **R-FCN** | **SSD**

- State of the art convolutional neural network algorithms such as Faster R-CNN, R-FCN and SSD are implemented.
- Faster R-CNN uses fast neural net instead of selective search algorithm for generating region proposals [6].
- R-FCN, shares 100% of the computations across every single output [7].
- SSD skips the region proposal step, instead considers every single bounding box in every location of the image simultaneously with its classification [8].
- In general, Faster R-CNN is more accurate, while R-FCN and SSD are faster.



Faster R-CNN



R-FCN

	Faster R-CNN	R-FCN	SSD
FPS	0.16	0.19	3.64
Accuracy	95.80%	91.50%	75.9%

Classification Performance

SSD

DISCUSSION OF THE RESULTS

- Rectified fisheye image increases the accuracy of the obstacle detection.
- Successful image stitching is achieved from multiple views by solving image registration through computation of homographies between images.
- Automatic image stitching is achieved up to 230 degree due to the artificial features of Truck Maker.
- SSD algorithm is the fastest algorithm in terms of FPS while Faster R-CNN algorithm is the most accurate one.

CONCLUSION

- Full visual coverage around the truck is obtained by using 4 cameras.
- Distorted fisheye images are rectified using polynomial distortion model and optimization.
- State of the art obstacle detection and classification algorithms such as Faster R-CNN, R-FCN and SSD are implemented, and average classification accuracies of 95.8%, 91.5% and 75.9% are obtained respectively.
- As a future work, developed system will be tested on a real truck.

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