

Automated Vehicle: Autonomous Driving using SVM Algorithm in Supervised Learning

Dr. K. Velmurugan Professor (Senior Grade)¹,
 B. Mathumitha², B. Merylen Jenow³, R. Thamizh Oviyam⁴
 Department of Computer Science and Engineering,
 Anjalai Ammal Mahalingam Engineering College,
 Koyilvenni, Thiruvavur-614 403, Tamilnadu, India.

Abstract:- Determination of suitable path for autonomous vehicle that is collision free between initial and end position through a workspace in presence of obstacle is challenging for autonomous vehicle design. Conceptual wise the word “Autonomous” associated with a machine means “a system that works without any intervention of human being” hence in today's era majority of the jobs are replaced by robots for performing numerous tasks i.e. manipulating objects from one place to another, path covering with detection of safe paths and welding etc. Extra feature of bumpiness detection is added to the existing system. A* search algorithm is used for path planning and decision making for autonomous vehicles in urban environment enable self-driving car to find safest, most convenient and beneficial route. Finally for classification of bumpiness, the proposed approach SVM classification algorithm is applied for classification of road severity.

Keyword:- Machine Learning, Support Vector Machine Classification, Supervised Learning, Obstacle Detection, Path Planning, Bumpiness Detection, A* search algorithm.

I. INTRODUCTION

An autonomous vehicle is the one that can guide itself without human conduction. This kind of vehicle has become a concrete reality and may pave the way for future systems where computers take over the art of driving. Since the 1990s – a time when autonomous driving was still only found in science fiction books or films – BMW engineers and technicians have been working on driver assistance systems. In the next decade, the car industry will change more drastically than it has over the past 30 years, because today we are standing at the entrance to a new era – of highly automated driving. Fully-driverless tech is still at an advanced testing stage, but partially automated technology has been around for the last few years. Functions that make partial automation possible are already a reality and installed in the latest BMWs on the street. Semi-autonomous driving assistance systems, such as the Steering and Lane Control Assistant including Traffic Jam Assistant, make daily driving much easier. They can brake automatically, accelerate. With the remote-controlled parking function, BMW made it possible to pull into tight spots without a driver for the first time. With so much investment and interest in driverless technology, it's easy to assume that self-operating cars are imminent, but they're much further away than we might think. Using

sensors to read the road like humans had their own limitations. Sensors are vulnerable to extreme sunlight, weather or even defective traffic lights. Henceforth analysing the images came into existence. For this process we are in need of machine learning.

In this paper we have used supervised learning to classify the level of bumpiness for rural environment. The image is obtained and transformed into a grid file. The Grid image file is processed using the CV2 which is available as a separate module in python especially for processing the image. A* search algorithm is used for finding the minimum path in the grid. The minimum path is provided as a result.

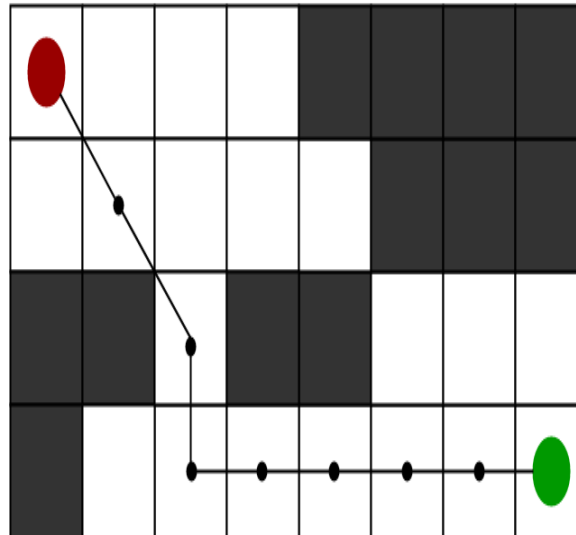
For an autonomous vehicle 3 modules are required. They can be listed as 1) Obstacle detection module 2) Path planning 3) Bumpiness detection. We have discussed the obstacle detection module in section 1, on how it processes the image and marking the position of the obstacle. Path planning module is described in section 2, about how it finds the minimum path to the goal with A* search algorithm. Bumpiness detection is depicted in section 3, on how it adjusts speed according to the rate of bumpiness of the road. Section 4 describes the architecture of the system and finally section 5 concludes the paper with a summary of the work

II. RELATED WORK

From Dixit VV, Chand S, Nair DJ (2016) Autonomous Vehicles: Disengagements, Accidents and Reaction Times. PLOS ONE 11(12): e0168054. Fully automated cars will allow drivers to be driven by an informatics system in their own vehicle, which facilitates the drivers to engage in non-driving related activities. However, under unfortunate situations of system failure, the drivers are expected to react in an appropriate and timely manner to resume manual driving. It is essential to understand the causes for disengagements and the resulting driver reaction times as the AV technological development is at full pace. The data from the first year of reporting from the autonomous vehicle trials in California have provided insights into disengagement and accident exposure, perception-reaction time and trust. Autonomous miles driven were found to have significantly high correlation and trends with accidents, suggesting that this quantity can be potentially used as a measure of exposure for disengagements and accidents.

- d) for each successor
- i) if successor is the goal, stop search $g = q.g +$ distance between successor and q
- $h =$ distance from goal to successor $f = g + h$
- ii) if a node with the same position as successor is in the OPEN list which has a lower f

- than successor, skip this successor.
- iii) if a node with the same position as successor is in the CLOSED list which has a lower f than successor, skip this successor
- otherwise, add the node to the open list .
- end (for loop).
- e) push q on the closed list end (while loop)



What A* Search Algorithm does is that at each step it picks the node according to a value-‘f’ which is a parameter equal to the sum of two other parameters – ‘g’ and ‘h’. At each step it picks the node/cell having the lowest ‘f’, and process that node/cell.

g = the movement cost to move from the starting point to a given square on the grid, following the path generated to get there.

h = the estimated movement cost to move from that given square on the grid to the final destination. This is often referred to as the heuristic, which is nothing but a kind of smart guess.

Here we use Euclidean distance to find **h**.

$$h = \sqrt{(current_cell.x - goal.x)^2 + (current_cell.y - goal.y)^2}$$

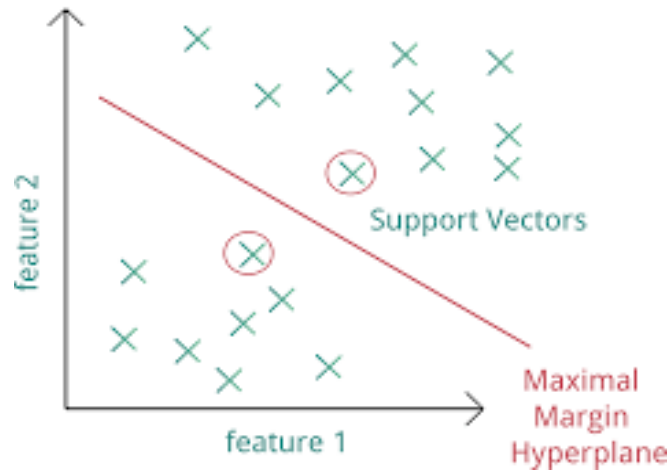
3. BUMPINESS DETECTION

For Bumpiness level detection Support Vector Machine (SVM) algorithm is used. Support vectors are data points that are closer to the hyper plane and influence

the position and orientation of the hyper plane. Using these support vectors, we maximize the margin of the classifier. Deleting the support vectors will change the position of the hyper plane. These are the points that help us build our SVM. In SVM, we take the output of the linear function and if that output is greater than 1, we identify it with one class and if the output is -1, we identify it with another class. Since the threshold values are 1 and -1 in SVM, we obtain this reinforcement range of values [-1,1] which acts as margin. To implement the SVM algorithm we use the Scikit learn library and just call the related functions to implement the SVM model. The number of lines of code reduces significantly too few lines than the normal program without using the library.

SVM algorithm is used to draw a hyper plane between the classified set of classes. In our case the classes would be fast and slow. Based on the ups and downs the classification is done. According to this classification the speed control system is instructed about the rate of speed that should be followed.

Support Vector Machines



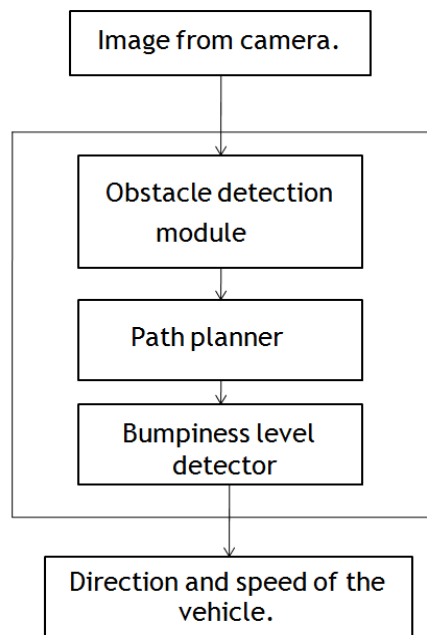
4. ARCHITECTURE

The system architecture comprises of above described modules with input and output of the system.

The input is given a frame of the video stream from the camera. That frame is processed by the system

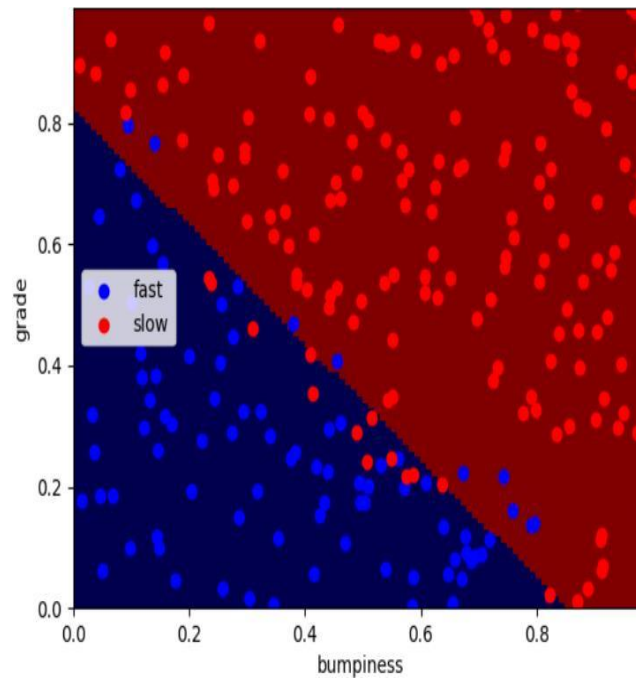
for detecting the obstacle and finding an obstacle free minimum path.

The system architecture is depicted as follows:



IV. RESULT AND IMPLEMENTATION

Classifying the bumpiness level with the SVM algorithm had resulted in an accuracy of 92% which is optimal than any of the classification algorithms.



The length of the code is also reduced in obstacle detection with the help of ImageAI module which adds efficiency to the system.

V. CONCLUSION

These labeled data were then used as training and testing data in a supervised learning algorithm (SVM) to establish a decision boundary. This decision boundary can then be used to automatically classify bumpiness level as high or low. In this paper we only

used two features, but this concept can be extended to many additional features. The data were limited in this article for illustration purposes.

At present, in case of SVM algorithm works in real-time on on-board computers. In urban environment, the operating speed of cars is one magnitude greater, so it requires special computers designed for autonomous driving for real-time running. Further possibility for speeding up our method can be the differential processing of roads.

ACKNOWLEDGEMENT

We have taken efforts in this project. However, it would not have been possible without the kind support and help of many individuals and organizations. We would like to extend our sincere thanks to all of them.

We would like to express our very great appreciation to Dr.K.Velmurugan, Head of Computer Science Department for his valuable and constructive suggestions during the planning and development of this research work. His willingness to give his time so

generously has been very much appreciated. We would also like to extend our thanks to the technicians of the laboratory of the Computer Science department for their help in offering us the resources in running the program.

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