# Road Following and Obstacle Avoidance System for an Unmanned Ground Vehicle

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**Abstract:** This research project aims to create an autonomous vehicle that can navigate along the specified route. Using the intelligent decision system, the vehicle can avoid obstacle and follow the road even without explicit structural landmarks such as lines or markers. The teaching and playback technique is implemented in the navigation system of the autonomous vehicle. During the teaching phase, the vehicle is driven by a human driver. The data from various kinds of sensors are collected and analyzed to create the estimate trajectory that will be used for the playback mode. In the playback phase, the vehicle's decision system uses the sensor data to control the vehicle according to the estimate trajectory from the teaching phase. The vehicle was tested at the average speed of 10 km/hr. The multi-sensor localization system can enhance the robustness of the navigation even when the low-quality data from GPS were received. The obstacle avoidance algorithm performed successfully when the obstacle has distinct color compared to color of the road.

**Keywords:** Unmanned Ground Vehicle, Autonomous Navigation, Road Following, Obstacle Avoidance, Teaching-and-playback

## 1. INTRODUCTION

Human driving is affected by many risk factors such as driver fatigue, bad visibility and intoxication. We have created a vehicle with an intelligent navigation system in order to assist human driving and eventually replace it in the future. This research project aims to create an autonomous vehicle that can navigate along a specified route. Using an intelligent decisioning system, the vehicle can avoid obstacles and follow the road even without explicit structural landmarks such as lines or markers.

An unmanned ground vehicle or UGV is a vehicle that can be navigated autonomously along a specified path or to a given destination. In the DARPA Grand Challenge 2005 autonomous vehicle competition, the team 'Stanley' from University of Southern California won the competition by successfully navigating more than 60 miles in the Nevada desert [1]. Stanley's vehicle was modified from a Volkswagen Touareg. This vehicle was controlled by an onboard computer based on information about the environment perceived via various sensors including laser ranging radar (LIDAR), camera and GPS. The machine learning algorithm was used to combine information from various sensors in order to understand the condition of the road and to navigate the vehicle along a safe path with an appropriate speed.

The autonomous navigation system for any UGV would require an ability to estimate the current absolute position of the vehicle as well as to identify an obstacle-free path immediately ahead of the vehicle. Multiple sensors are generally used to gather information of the vehicle position and the condition of its surroundings. Most research in the field of autonomous UGV's has been focused on using machine vision technology to identify road lanes and obstacles. The early work from Carnegie Mellon University [2] applied neural networks to road detection using a monocular camera system. Beauvais and Lakshmanan [3] used radar together with image information to identify road lines and obstacles. Apostoloff and Zelinsky [4] used active stereo vision to capture both near field and far field images to add to the ability of the system in identifying road condition at various distances. Georgiev and Allen [5] proposed a method of using an Extended Kalman Filter to combine odometry information together with compass and GPS sensors, then using image information to assist whenever the uncertainty is high.

The method we use in our autonomous navigation system is a combination of a localization process, road following and obstacle avoidance. The localization process is based on information from various sensors including GPS and odometry, while the road following and obstacle avoidance process is based on information received from multiple cameras.

One weakness we found in many methods for processing images is the usage of pixel thresholding and threshold values to do segmentation and other classification processes. Since image data is inherently continuous, any algorithm based on thresholding is subject to instability when measured values approach the thresholds. Throughout our methodology, we were careful to avoid the usage of any discontinuous thresholding. This approach results in a continuous space at each stage of processing, resulting in stable performance of the system under changes in environmental conditions.

## 2. METHODOLOGY

### 2.1 Unmanned Ground Vehicle

The 'Darkhorse' unmanned ground vehicle (UGV) as shown in figure 1 has been designed and built by the team of mechanical engineering student from the mechanical engineering department at KMUTT. This vehicle is powered by a motorcycle internal combustion engine with an automatic transmission (110 CC/ 8 HP). Various kinds of sensor are used in this system. The encoder is attached to the right rear wheel for measuring the distance and the velocity of the vehicle. Another encoder is attached at the steering wheel to measure the turning angle. An Inertial Measurement Unit (IMU) which consists of three gyroscopes and three accelerometers is used to measure angular velocity and acceleration, respectively. The ultrasonic sensors are attached in front of the car in order to detect a close-range obstacle. Global Positioning System (GPS) is also used to acquire the global position of the car. Up to four GPS modules are used in the system. Two cameras are installed for road tracking as well as detecting obstacles, traffic lights, and traffic signs.

**Fig. 1** Darkhorse UGV

### 2.2 Sensor and Actuator System

The low-level control system of the vehicle can be divided into 3 subsystems: the steering, the brake and the throttle systems. All systems are driven by DC motors. The three subsystems are connected to the high-level control system in the on-board computer via RS-232, as shown in the diagram in fig 2.

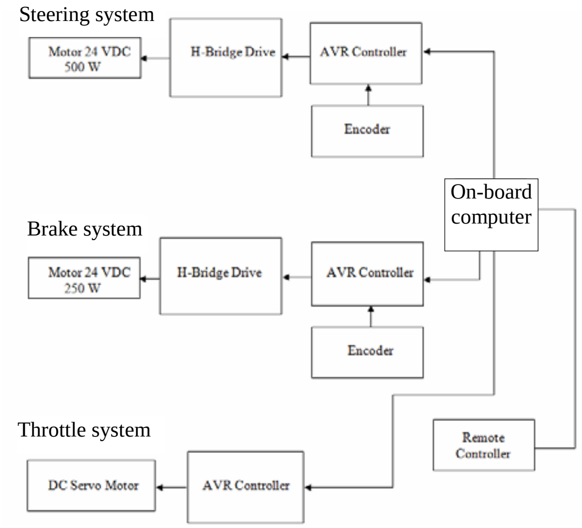
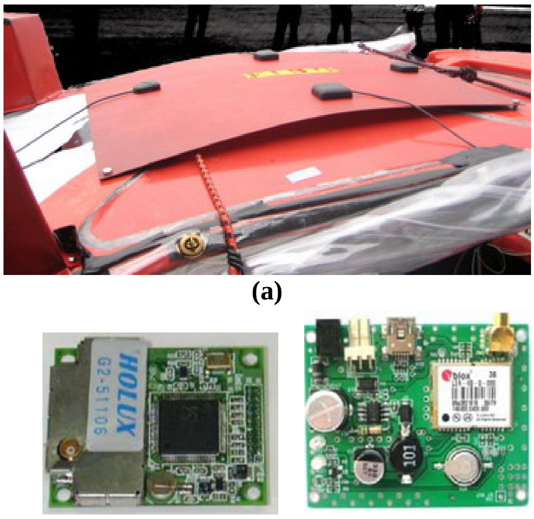



**Fig. 2** Actuation System

The sensor system on the vehicle is comprised of cameras, GPS modules and odometry sensing modules. Two cameras are installed on top of the vehicle as shown in fig.3. An image from the left and the right cameras are combined to give the full view of the road ahead with sufficient detail up to approximately 20 m. Four GPS modules are used with separate antennas installed on a metal sheet attached to the roof of the vehicle which provides a backplane for the antennas. Different brands of GPS modules were used: 3 Holux brand and one Ublox brand module. Multiple GPS modules allow more accurate position estimation due to the redundancy of information especially when multi-path errors occur. GPS modules provide absolute position information including latitude, longitude, speed and heading. Two encoders, one on the rear wheel and one on the steering column, provide odometry information such as distance traveled and speed of the vehicle as well as steering angle.

**Fig. 3** Two cameras were installed on top of the vehicle




(a) (b) (c)

**Fig. 4** (a) Four GPS modules of two different brands were installed on the vehicle (b) HOLUX (c) Ublox

## 3. AUTONOMOUS NAVIGATION SYSTEM

The autonomous navigation system is comprised of two phases: the teaching phase and the playback phase. In the teaching phase, a human driver drives the vehicle along the desired route. During this phase, the localization system aggregates all of the sensor information and records the trajectory based on the estimated position of the vehicle. In the playback phase, the autonomous system uses the recorded trajectory as the reference trajectory for rough vehicle navigation, while the lane tracking and obstacle avoidance systems handle the fine control of the vehicle so that it stays on the road and does not collide into any obstacle. The system diagram of the autonomous navigation system is shown in figure 5.

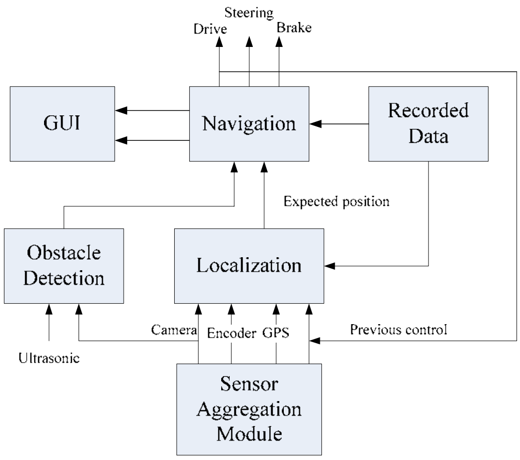



**Fig. 5** System diagram for the autonomous navigation system

**3.1 Sensor Aggregation Module**

An encoder at the steering column and another at the rear wheel provide readings for steering angle and the wheel rotation velocity to the localization module. The current position of the vehicle is updated according to this odometry information. All GPS modules provide latitude and longitude as well as speed and heading angle of the vehicle. The information from each GPS module is received at a frequency of 1 Hz.

**3.2 Localization System**

The localization system receives update from the encoders and calculates the current estimated position of the vehicle relative to the initial position based on the mathematical model of the vehicle. When the information from the GPS module is received, the current absolute position of the vehicle is updated. The estimate position of the vehicle was recorded in the teaching phase to create the reference trajectory for the autonomous playback phase. In the playback phase, the localization system provides the current estimate position of the vehicle to the autonomous navigation system to be compared with the reference trajectory as recorded in the teaching phase. This paragraph explains the position estimation algorithm.

**Fig. 6** GUI shows the current estimated position of the vehicle (green rectangle on the lower right corner) on the recorded trajectory (green line)

**3.3 Navigation and Obstacle Avoidance System**

In the autonomous navigation system, the current absolute position of the vehicle is compared to the nearest position in the reference trajectory within a specified time window. The error between the current position and the reference position is used to create a rough navigation decision for the vehicle control system.

However, the rough navigation decision from the current estimated position is not sufficient for guaranteeing that the vehicle will stay on the road. The absolute position information from the GPS can have an error that is larger than 5 m which does not provide enough accuracy for the localization module to be used to control the vehicle on a road that is 5-10 m wide. Therefore, image information from multiple cameras is used to evaluate the road area ahead of the vehicle. Fig.7 shows the captured images from the left and right cameras which can be combined to give a full view of the road ahead.

**Fig. 7** the captured images from the left and right cameras

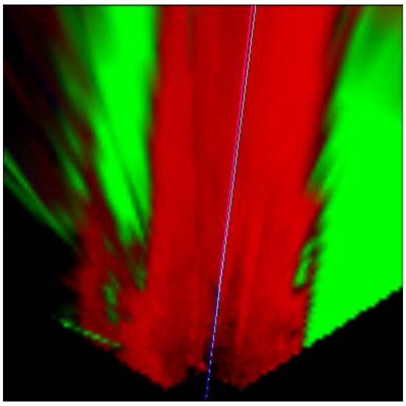


**Fig. 8** the projected images from the left and right cameras after the scoring process (the red-channel represents the score associated with the dirt road, the green-channel represents the score associated with the grass, the blue line indicates the optimal chosen path)

After the images are captured, a scoring function is applied to each cluster of pixels in the image to convert the RGB color values into a series of quantitative scores to determine the relative likelihood that a given region is road, grass, cement, or other known obstacle type. By assuming that the surface of the road in front of the vehicle is flat, we can remove the perspective from these scoring images by projecting them onto a hypothetical flat ground plane immediately ahead of the vehicle. While objects such as obstacles are not actually flat on the road, since their lowest point is resting on the road, this projection still works by accurately placing the lowest part of the obstacle in its correct location on the ground plane while the projection of the upper parts onto the flat plane only create inaccuracies further away. This can be accommodated easily by accounting for this in the control algorithm.

We assign an avoidance value to each of the scored object categories and then accumulate the product of the scoring values mentioned above times the avoidance value associating with that category of surface. These avoidance values reflect a subjective priority of importance on avoidance of a given type of object and are conceptually similar to a potential field approach. In our experiment we used the values listed in table 1.

**Table 1** The avoidance value

| | Avoidance value |
|---|---|
| Initial score | 0.5 |
| Road | -1.5 |
| Grass | 3 |
| Cement | 1 |
| Known obstacle | 2 |

For example, if a given region of ground in front of the vehicle was computed to have a road score of .7, a grass score of .05, a cement score of .07 and all known obstacle scores to be 0, then the aggregated avoidance score would be 0.5 + .7*(-1.5) + .05*3 + .07*1 + 0*2 = -.33. A lower avoidance score value suggests that the vehicle does not need to avoid that region while a higher avoidance score value suggests that such a region should likely be avoided.

A region growing algorithm is employed to grow higher avoidance areas into lower avoidance areas to account for the size of the vehicle. This is similar to a typical C-space transformation although performed on the continuously variable avoidance scoring values rather than a binary occupation grid. The image of the avoidance value after the region growing is performed is shown in fig.9.

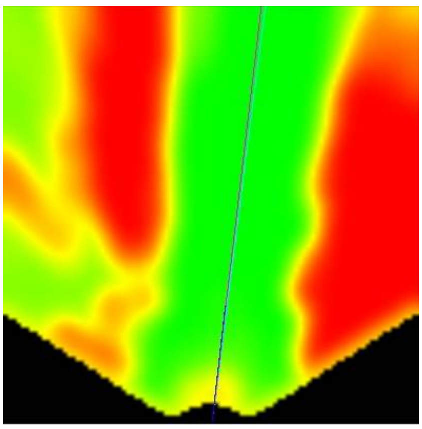


**Fig. 9** the projected images of the avoidance value (green represents a low avoidance value and red represents a high avoidance value)

In order to compute a control value for both throttle and steering, the avoidance score value can be accumulated over a given path to determine the overall avoidance score of that path. By comparing the overall avoidance score between a number of different paths, the most suitable path can be chosen as the one with the lowest avoidance score. The steering angle is set in order to follow the initial optimal path vector, while the throttle command is chosen based on the magnitude of the overall avoidance score for this path.

## 4. RESULTS AND DISCUSSION

The Darkhorse UGV was tested at KMUTT football field and the Bangkok Racing Circuit (BRC). At KMUTT football field, the vehicle was driven around the football field on a dirt track during the teaching phase. The vehicle was then autonomously controlled in the playback mode guided by the reference trajectory as explained in section 3. The estimated position in the teaching and playback phases are shown in figure 10. Fig. 11 and 12 show the GPS position of the four GPS modules recorded simultaneously which are overlaid on top of the satellite image during the teaching phase and the latitude and longitude plot during the playback phase to show that the error of the GPS readings can largely degrade the accuracy of position estimation. Even when the position estimation is degraded, the vehicle successfully negotiates the path by using the camera information to remain on the track.

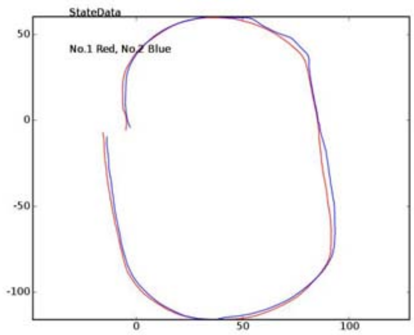



**Fig. 10** the estimated position in the teaching (red line) and autonomous playback (blue line) phase

**Fig. 11** the GPS position of four GPS's and the estimated position overlaid on top of the satellite image of the KMUTT football field during the teaching phase

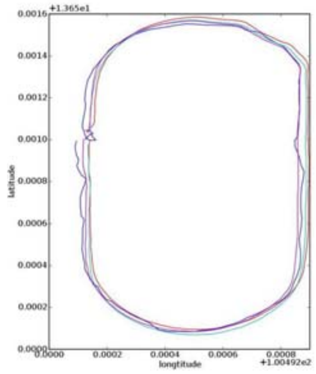



**Fig. 12** the GPS position of four GPSs during the autonomous playback phase

In order to test the performance of the obstacle avoidance feature in the navigation system, a red plastic board sized 1.5m x 1.5m was placed in the middle of the road at the BRC as shown in Fig.13. The roads at the BRC have a dark gray color with grass and sometimes cement on the side of the road and sometimes cement patches in the road. Figure 14 shows an example of the ground-plane projected avoidance score image computed from both camera views. The red region on the left corresponds to a grass area on the left side of the road and shows a high avoidance score while the red region on the right corresponds to an obstacle in the road. The system computed an optimal path that avoids the obstacle on the right without going into the grass on the left.

**Fig. 13** the red obstacle was placed in the middle of the road at Bangkok Racing Circuit

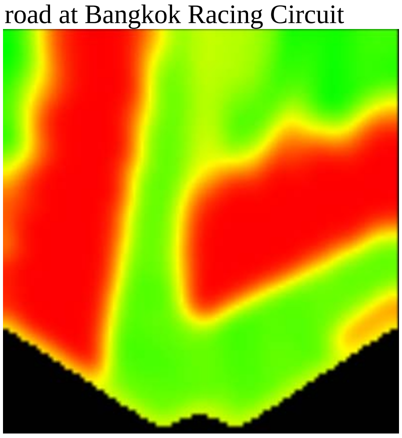


**Fig. 14** the projected images of the avoidance value when the red obstacle was visible in the image (green represents a low avoidance value and red represents a high avoidance value)

From the tests at both KMUTT and the BRC, the Darkhorse UGV vehicle successfully stayed on the road and avoided obstacles that can be visually distinguished from its surroundings such as a red or green plastic board at an average speed of 10 km/hr. Using the same previously recorded route and settings, these tests have been performed on different days at various times from 7 am to 6 pm, demonstrating that the autonomous navigation system is sufficiently robust for different lighting and environmental conditions.

## 5. CONCLUSION

The Darkhorse UGV was developed to be an autonomous ground vehicle that can navigate along a recorded trajectory that was previously driven by a human driver. The autonomous navigation system of this vehicle is based on a teaching and playback system. In the teaching phase, the trajectory is recorded from the estimated position of the vehicle based on various sensors. In the playback phase, the current estimated position is compared with the reference trajectory to give the rough control decision. The image information is used to perform a finer level control so that the vehicle can stay on the road and avoid obstacles while still generally following the reference trajectory. The fine control decision is determined by comparing an avoidance score metric over the set of possible immediate path options. The overall autonomous navigation system performed successfully by navigating the vehicle along various routes while avoiding obstacles.

## 6. ACKNOWLEDGMENTS

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