Progress and Prospects for Vision-Based Automatic Driving

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Introduction

Automatic driving -- if it were possible and if it were fully implemented -- could yield great benefits. Automatic driving systems could increase the throughput of the nation's freeways, improve safety, and provide transportation services to millions of people who are currently without them.

The most immediate benefits would be in increasing throughput on congested freeways. High occupancy vehicle (HOV) lanes have already demonstrated the ability to increase the carrying capacity per lane of traffic. The technology already exists to permit platooning of specially equipped vehicles on restricted access, specially equipped, HOV lanes. The PATH program in California has demonstrated that vehicles can reliably follow magnetic spikes buried in the roadway and maintain close vehicle spacing at highway speeds using a combination of radar and intervehicle communication. Others have demonstrated vision-based road following and vehicle following techniques at highway speeds. Of course, many problems remain to be solved. Limited access lanes are expensive, and there are many questions of how to accomplish ingress and egress from moving platoons.

Safety would also be an important benefit. By far the largest single cause of highway accidents is human error. If even a small percentage of traffic accidents could be prevented, the cost in terms of property damage, medical care, pain and suffering, and lost lives would be significant. Unfortunately, the technology for automatic collision detection and avoidance is much further from realization. Collision avoidance systems based on radar are subject to both false alarms and to failure to detect many types of potentially dangerous situations. Reliable general-purpose collision detection and avoidance systems will almost certainly require at least some vision-based technology.

Vision-based automatic driving on ordinary roads and streets would provide access to transportation services that would greatly enhance the lives of many aged and handicapped persons. Unfortunately, general purpose automatic driving is an extremely difficult and technically challenging problem. It will undoubtedly be many years before vision-based technology for general purpose driving will be feasible. Technology far more sophisticated than anything available even in the most advanced research laboratories will be necessary.

The purpose of this paper is to review some of the progress in the field of vision-based driving and assess the prospects for the future. There has been, and continues to be, a great deal of research in this field. Much of the funding in this country has been provided by the DARPA Image Understanding (IU) program, the Autonomous Land Vehicle (ALV) project, and the current Unmanned Ground Vehicle (UGV) program. Funding for the UGV program has also come from the Office of the Secretary of Defense and the Army Laboratory Command. These programs involve research efforts at several universities including Carnegie Mellon University, University of Maryland, the University of Massachusetts, as well as at the National Institute of Standards and Technology and a number of private companies. NASA has sponsored planetary vehicle driving research research at the Jet Propulsion Laboratory. Recently the Federal Highway Administration has provided some funding for research in autonomous highway driving as part of their Advanced Vehicle Control Systems (AVCS) program.

In Europe, the Prometheus project has provided a large amount of funding over the past decade for research in vision based automatic driving. The most advanced of this work has been done at the Universitat der Bundeswehr Munchen [15]. In Japan, a number of IVHS projects are in progress. Toyota has demonstrated vision-based lane following, lane changing, and passing [34].

The Technologies of Vision Based Driving

The primary challenge in autonomous driving is the development of image processing techniques that are reliable under the extreme variability of outdoor conditions in a variety of environments. Roads can vary tremendously in appearance. Some are smooth and well marked while others are riddled with cracks and potholes or are not marked at all. Shadows, glare, varying illumination, dirt or foreign matter, other vehicles, rain, snow, etc. also affect road appearance.

To address these challenges, perception for autonomous driving has been approached with a wide variety of vision-based techniques. Most of these approaches fall into one of two categories: region-based statistical classification methods and feature tracking methods. Other methods based on neural networks have also been proposed.

Statistical classification methods

Statistical classification methods [1], [2], [4], [6], [7], [8], [9], [10] have been applied to the road perception problem. These methods share a similar paradigm that involves classifying each pixel as either road or non-road. This is done using classical techniques of supervised or unsupervised statistical classification [30]. Road shape is usually then determined by finding the closed region that contains the highest concentration of "road" pixels.

In all these methods, each pixel is classified on the basis of its color. In addition, [1] uses a measure local texture and [10] uses the image coordinates of the pixel. The color at each pixel is measured in terms of three scalar components: red, green, and blue (RGB). SCARF [1], [2], [4] and UNSCARF [10] and FMC [7], [8] directly use the three RGB color components for classification. VITS [6] uses red and blue only. Lin and Chen [9] base classification on the values of hue, saturation, and intensity (HSI). The HSI representation is computed by a non-linear transformation from the measured RGB values. Lin and Chen claim that the HSI representation is better suited for road segmentation.

Classification involves assigning each pixel to one of a number of predefined classes. VITS, FMC, and Lin and Chen classify all pixels as one of two classes: road and non-road. SCARF and UNSCARF represent road and the non-road each by multiple classes. The rationale for having multiple classes is to better represent the variation in outdoor scenes. For example, the differences in color among portions of the road that are wet, shaded, sunny, patched, etc. are significant and are therefore probably better accommodated by separate classes rather than being lumped into one class.

Supervised classification

Most of these approaches [1], [2], [4], [6], [7], [8], [9] use a form of supervised classification. In supervised classification, the statistics of each class are known prior to classification. Each pixel is then assigned to the class which it most closely matches in the statistical sense. SCARF represents each class by its second order statistics, that is in terms of its mean and covariance. VITS, FMC, and Lin and Chen divide feature space by a planar boundary between the road class and the non-road class and thereby implicitly assume that the two classes have equal covariance.

It has been reported that fixed class statistics are not consistently reliably for supervised road classification. For example, the statistics that accurately segment a portion of a road on a sunny day may not yield a reliable segmentation on a cloudy day. To address this problem, these methods continually recompute class statistics during operation. After each image is classified, the classified pixels are then used to compute the class statistics that will be used for classifying the next image.

The initial class statistics can be established in various ways. The FMC classifier is initialized automatically. The first image is segmented into regions. The pixels in each region are then used to compute the initial class statistics. Other methods require a human operator to label regions in the initial image by hand.

Once all the pixels have been classified various techniques can be used to find the boundary which seems to best represent the road. SCARF uses a Hough method where each pixel votes for all values of the road shape parameters that are consistent with the location of the particular pixel. The parameter set that receives the most votes is chosen as the road model. VITS and FMC determine the road boundary by finding the edges between road from non-road regions.

SCARF has been used to navigate the CMU NAVLAB along bicycle paths, dirt roads, gravel roads and suburban streets at slow speeds. In particular, SCARF has been successful in locating roads that are obscured by heavy shadows. SCARF encounters problems when the road is covered by leaves or snow. When this happens, a road class and non-road class become indistinguishable. Problems are also encountered when there are large changes in illumination between successive images. As far as computation time, SCARF's image processing requires on the order of one second per image depending on the hardware configuration [1].

FMC reports achieving real-time road following on dirt, gravel and paved roads at speeds up to 19 km/h using their vehicle, a specially instrumented armored personnel carrier. They reported that their system does not reliably classify areas of road that are in shadow or that contain puddles or patches [8].

VITS was able to successfully navigate the ALV over a 4.2 km paved test track at speeds of 10 km/h [6].

The strength of these methods is their generality. They do not require lane markers to be painted on the road and they do not require a crisp or smooth road boundaries. A potential weakness of this approach is the method of recomputing class statistics. There is a cyclical dependency between segmentation and the road statistics. If the segmentation is incorrect, the pixels that were misclassified will contaminate class statistics. Inaccurate class statistics will then lead to poorer segmentation. Therefore, the system will probably not recover once it misinterprets an image. This approach also requires continuity in road appearance between successive images. For instance if the sun goes behind a cloud the color statistics computed from the image of the sunny road probably will not produce a good segmentation on the image in which the sun is hidden.

In practical terms these methods also require large amounts of computation and therefore are slow in processing each image. Because of these demands, these methods have not been able to achieve high speed speed driving.

Unsupervised classification

The techniques described above are examples of supervised classification. Pixels are grouped in to categories whose statistics have been pre-specified. In unsupervised classification, no prior categories exist. Instead categories are formed by grouping together pixels into natural clusters. Pixels that are similar are grouped together. A method called UNSCARF [4], [10] uses this technique for road recognition. It groups sets of pixels into regions of similarity and then selects the set of regions whose combined shape best forms a road. To cluster pixels, a variation on the ISODATA clustering algorithm is used [30]. In this method each pixel is first arbitrarily assigned to a class. The mean and covariance of these classes is then computed and the pixels are reclassified to the class for which its Mahalanobois distance is minimum. The statistics for these classes are then recomputed using these pixels that have been re-assigned. The pixels are then reclassified again and the whole process is repeated.

Feature Tracking Methods

Feature tracking methods [2], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [25], [35], [36], [37], [39] locate the road on the basis of distinct features, usually the lane markings painted on the road or the boundary between the road and its surroundings. To locate these features, feature tracking methods exploit the temporal continuity of the image sequence; that is, the search for each feature is constrained by the feature's location in the previous image. Feature tracking methods typically maintain a geometric model of the road that is updated over time. The differences between various feature tracking methods, lie in how the features are detected, how the road is modeled, and how the road model is updated.

The VaMoRs system of Dickmanns and Graphe [11], [12], [13], [14], [15], [16] was one of the first systems to demonstrate autonomous road following at high speeds. This system is based on locating road boundaries and road lane markers. These features are detected in the image using edge extraction. In the neighborhood of predicted feature location, the image is correlated with edge masks in a range of orientations about the predicted edge orientation. These extracted edges are then considered to belong to a feature if they form line features with low curvature, are parallel to other line features, and are almost parallel to the viewing direction. In addition to vision, the vehicle motion is measured by internal sensors.

Using visual and vehicular measurements, the 3-D geometry of the road is reconstructed and updated for each new image. The complete model is comprised of 9 state variables. The road is modeled by 3 state variables representing the horizontal (lateral) contour of the road and 2 state variables representing the vertical (elevation) contour of the road. These contours are approximations to the clothoid model where curvature is modeled as a linear function of arc length. This model also includes 4 state variables representing vehicle steering angle, lateral offset from the center of the lane, heading angle, and slip angle.

Dickmanns and Graphe derived the state transition equation expressing the evolution of this 9-dimensional state vector over time. They combine this equation with knowledge of relationships between the measured quantities and the state to update the state after each new image is acquired. They use a Kalman filter-like approach to update the state.

The VaMoRs system has been able to achieve autonomous driving at speeds up to 100km/h and continuous driving of up to 20 km on the German Autobahn (this was actually demonstrated with an earlier version of their system that did not account for vertical curvature [11], [12].) They have also had success driving on various lighting and weather conditions and on unmarked cross-country roads.

A road following system developed at NIST [35] also tracks lane markings. The markings are located using edge extraction and each set of lane markings is fit to a second order polynomial in the image plane. This fit is computed over time using exponentially weighted recursive least squares. The data from each image is weighted in this filter formulation as a function of the confidence in that data. This system has been used to autonomously drive a HMMWV at speeds up to 90 km/h. After testing on a limited set of roads the system gives reliable tracking on roads with solid lane markings in the presence of moderate shadows and non-ideal weather conditions, but is less reliable in the presence of heavy shadows and when lanes are marked with infrequently spaced dashed lines.

The YARF system, [2], [23], [24], tracks the lane markers and the shoulders. These features are detected on the basis of known geometry, known color, and edges. The road is modeled as a flat plane and all feature points are used to find a 2nd order polynomial that best describes the path of the road. Fit is computed using both least squares and least median squares. The least median squares approach gives superior performance in the presence of outliers, but is too computationally demanding for real-time implementation. YARF has been used to autonomously drive the CMU NAVLAB at speeds up to 25 km/h on a public roads that included high curvature curves and shadowing from surrounding trees.

The University of Maryland system [17], [18], [19], [20], [21], [22] is based on identifying the road boundary using edge detection. This method searches for the road beginning at the bottom of the image. A small window at the bottom of the image is searched for the road. This search area is chosen based on the location of the road in the previous image. Once the location of the road is found in the window, other windows are placed above this window and searched for road. This process continues moving from the bottom to the top of the image. This system has achieved autonomous road following over a distance of several hundred meters at a speed of 3 km/h using the Martin Marietta Autonomous Land Vehicle. The system does not work well in the presence of patchy roads, shadows, and water on the road.

A system developed by Toyota [34] uses edge extraction to locate the lane markings. This system has been able to achieve autonomous driving at speeds up to 50 km/h. Successful driving has been achieved on both sunny and cloudy days, and in the presence of shadows. The system is less reliable under more severe lighting and weather conditions including sunrise, sunset, and heavy rain.

The University of Bristol has developed a system [25] based on edge points of the road boundary. The edge points are fit to a 2nd order polynomial. All points that are three sigma away from the polynomial are discarded and the least squares computation is recomputated. This process of computing points and discarding outliers is repeated until the variance stops decreasing. This method has been used to autonomously drive a small electric vehicle on paths on the university grounds.

Others have worked with feature tracking approaches for driving in simulation. These include [36], [37].

The advantage of the feature tracking algorithms is that they require less computation and are therefore able to achieve higher speed driving. The disadvantage is that they require specific features of the road infrastructure to be present such as clearly marked lane markers. When these features are not prominent due to wear, or are obscured because of weather or lighting, these techniques become unreliable.

Other Approaches

A neural network-based approach ALVINN [27], [28] has been developed at Carnegie Mellon University for autonomous driving. The input to the network is a reduced resolution 30 X 32 processed image. The network generates a steering angle as an output. The network is trained by using back propagation while a human is driving. To obtain a training sequence that includes a large variety of driving situations, several techniques are used. One is to add structured noise in image regions where the network may draw an incorrect correlation. For example, in a short training sequence, the network may draw a correlation between the amount of grass in view and the appropriate steering angle. This network may then fail when the grass becomes obscured by a guard rail.

ALVINN has successfully driven the CMU NAVLAB for a continuous run of 34 km. ALVINN has used to autonomously drive the NAVLAB at speeds of up to 88 km/h. ALVINN has been successfully trained for highways, unmarked rural roads, and cross-country roads.

Other approaches proposed for road following include image flow [26], morphological image processing [38], and combined region and feature extraction [40].

Discussion

A great deal of progress has been achieved, and new developments are rapidly being made. Vision-based lane following (lateral control) at highway speeds has been demonstrated on roads with clearly visible lane markings and no intersections. Vision-based car following (longitudinal control) in a platoon formation also appears to be within the state of the art, provided there is communication of acceleration information between vehicles in the platoon. This suggests that vision might offer a practical near term option for restricted applications such as platooning. Although much remains to be done, vision-based technologies may offer considerable advantages over alternative approaches to the problems of ingress and egress from moving platoons.

If nothing else, vision-based technologies could provide redundancy that would increase the reliability of platooning to the point where it could be implemented on ordinary freeway lanes without the expense of specially constructed roadways.

While vision-based systems are currently more expensive than competing technologies, prices of TV cameras and image processing hardware is falling rapidly and steadily. In five to ten years, vision-based lateral and longitudinal control systems for platooning may be very cost competitive.

Unfortunately, the next step of unrestricted automated freeway driving with lane changing, collision avoidance, and ingress and egress from the freeway itself is a much more distant goal. And the step beyond that, of general purpose automatic driving on two lane roads and city streets is very far in the future. While all of the systems described above are capable of road following, only a few seriously address the problem of obstacle detection and avoidance. There are no systems that offer promising solutions to the general purpose automatic driving problem.

About all that is clear is that vision-based technologies offer the only real hope for collision detection and obstacle avoidance for general purpose driving. For example, on curved roads, objects by the side of the road (such as trees, phone poles, or bridge abutments) often appear directly in front of the vehicle. On curved roads, radar collision avoidance systems cannot distinguish between objects by the side of the road and obstacles in the road. Only a vision system has sufficient resolving power to detect both the road curvature and the position of potential obstacles so as to decide whether a perceived object lies in the vehicle's lane or not. On two lane roads, on-coming traffic will often appear to a radar system to be on a collision course with the vehicle. Only a vision systems has sufficient angular resolution to distinguish between an on-coming vehicle in the left lane and one in the right lane. Only a vision system can track lateral motion of on-coming traffic with sufficient accuracy to determine whether an on-coming vehicle is going to cross into the right lane or not. At intersections, only vision systems will have sufficient angular resolution to track cars on intersecting roadways and predict whether or not they will cross into the path of the vehicle.

To achieve human levels of performance under all driving conditions will take a very long time. It will require machine vision systems to have performance that equals or exceeds the human vision system, at least within the task domain of driving a vehicle.

Human vision is an extremely complex and sophisticated system. The human eye has extremely high resolution in the fovea, with surrounding low resolution peripheral vision that covers nearly half the egosphere. The human eyes are balls driven by a set of muscles that stabilize the gaze and counteract accelerations due to rough road conditions. The eyes are carried in a head that is mounted on a neck and body so that it can swivel in all directions. The control system for the human eyes not only stabilize the gaze, but can quickly move it from one point of interest to another in roughly one tenth of a second. The human gaze can examine up to five different points of interest per second. This is a system of enormous sophistication, and that is just the visual pointing system.

The human visual processing system performs more computations per second than a Cray computer. The human eyes work in pairs to provide stereo vision that yields range information and gives a three-dimensional view of the world. The human vision system is also well adapted to analyzing motion in order to estimate range and velocity of moving objects in the world, and to compute time-to-collision or expected clearance for many objects simultaneously. It is not clear how the vision system does all this, or how it recognizes whether a dark patch on the road is a pot hole, a shadow, a blotch of tar, or a body lying in the road.

It will be many years before we are able to build machine vision systems that can match human vision for driving a vehicle -- but it will not be forever. Eventually, these problems will yield to solution as research continues.

In the mean time, vision-based driving is a field filled with promise. Vision is the primary sense used by human drivers, and the nation's roads and highways are designed and marked so as to assist the human vision system in performing the perceptual tasks necessary to safely drive their vehicles. If and when reliable and inexpensive machine vision systems are developed, the road and highway infrastructure will need very little modification in order to allow their use.

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