Town Digitizing-Recording of Street Views by using ODVS & GPS

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Abstract

Vehicle navigation and driver assistance systems can be aided with rich 3-D environmental models. In this paper, we describe a position indexed image-based environmental model that can be used to enhance vehicle navigation, carry out driver training, perform roadway surveillance, and serve as a virtual drive through system, among other tasks. Model building is accomplished by combining an omni-directional (i.e., 360 degree) imaging sensor with a high accuracy GPS positioning system. The data acquisition process is quite simple: the image sensor and GPS antenna are simply mounted on a vehicle and the vehicle is driven normally on the roadways of interest. The resulting database can then be used for a number of applications. This paper describes the details of such a system, along with experimentation that has been carried out in a 50 square kilometer region with a high density of roadways.

1 Introduction

In the last decade, there has been intensive research and development in the Intelligent Transportation Systems (ITS) arena, particularly in vehicle navigation and driver assistance systems. The aim of these systems is to improve comfort, safety, and mobility. These systems make use of a variety of sensors, including GPS-positioning, inertial navigation, ultrasonic sensors, and computer vision. Using a combination of these sensors can produce a local perception of the vehicle's environment. This perception of the environment can be exploited for various navigational tasks.

This environmental perception around a vehicle can be significantly enhanced when combined with some type of environmental model. For example, if perception of the local environment is used in conjunction with digital map information, prediction of the roadway ahead can occur. In addition to digital map information, a rich 3-D environmental model of the roadways can be useful for 1) previewing routes prior to traversing them; 2) guiding a driver along a particular route; and 3) transportation planning and management.

In this paper, we describe a method that exploits position-indexed imagery as the basis of an outdoor environmental model. In mobile robot research, building and using environmental models are common tasks for navigation and finding particular objects. These tasks are typically carried out indoors, and many modeling methodologies exist. Usually the indoor structures are simple and knowledge of these structures can be exploited. In an outdoor environment however, the structure is much more complicated and environmental modeling is a much more difficult task. Often image-based modeling is used. For example, Tsuji et al. [8] proposed a method for obtaining an outdoor environmental model based on route panoramic views.

For the roadway environment, we propose building image-based models that are indexed by position. For this task, we make use of an omni-directional vision sensor (ODVS) that is integrated with a high accuracy GPS positioning system. The ODVS captures 360 degree image data at the standard frame rate of 30 frames/second. Visual information in all directions can be acquired, while the imaging center is measured to within a few centimeters (x, y, z) using carrier phase GPS techniques. One of the key attributes of this technique is the ease of collecting the environmental data. The ODVS and GPS antenna are simply mounted on top of a vehicle, and the vehicle is then driven at normal speeds along all the routes of interest. The images are compiled into a database, where they can be indexed by their recorded position.

There are numerous applications that can use this

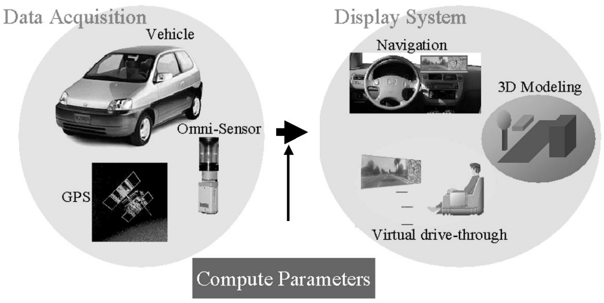


Figure 1: System Components

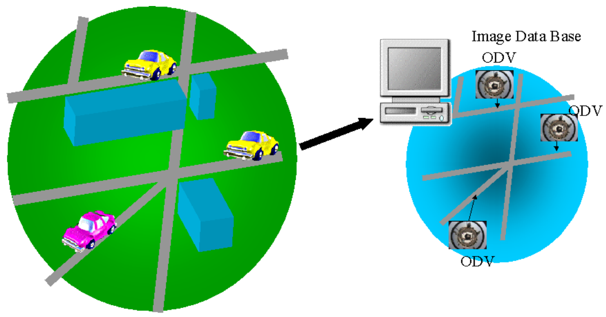


Figure 2: Data Acquisition System

type image-based environmental model. For example: 1) navigation systems; 2) virtual drive-through systems; 3) driver training; and 4) roadway surveillance.

In this paper, we describe this system in detail. Experimentation has been carried out showing the advantages of the technique.

2 System Description

The overall system consists of two components, as shown in Fig 1: 1) a data acquisition system; and 2) a display system. These two components are described below.

2.1 Data Acquisition System

In order to acquire the position-indexed omni-directional image database, an omni-directional vision sensor (ODVS) is mounted on the roof of an instrumented vehicle. The instrumented vehicle is equipped with a two-frequency GPS receiver that is capable of centimeter-level positioning accuracy using carrier-phase differential techniques [3]. The instrumented vehicle is simply driven on all of the roadways of interest and omni-directional image captures are triggered by the GPS receiver at a rate of 1 Hz. This process is illustrated in Fig 2.

2.1.1 Omni-Directional Vision Sensor

Omni-directional vision sensing is a powerful capability that can be used in a number of applications such as mobile robot navigation and surveillance techniques. Several omni-directional vision sensing methods and hardware exist as outlined in [5]. These methods can be categorized into various types, such as integrating views from multiple cameras, swiveling a camera by using a rotating table, and capturing single omni-directional images using different mirror shapes (e.g., spherical, conical, hyperbolic, etc.).

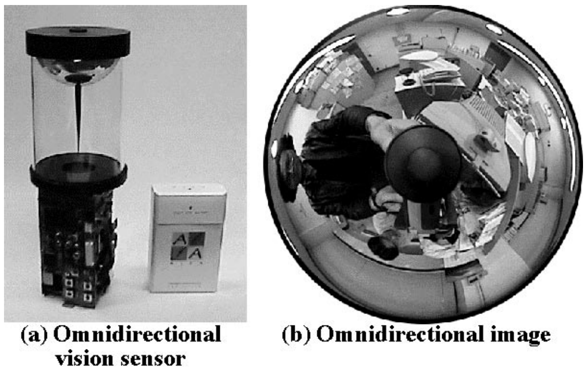
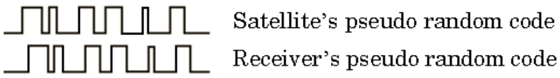
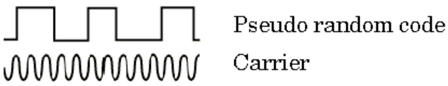


Figure 3: Omnidirectional Vision Sensor

To capture omni-directional images in dynamic outdoor environments, the mirror-based methods tend to be the most suitable. In our system, a 360 degree image is captured by pointing a standard NTSC video camera coaxially towards a hyperbolic mirror, as is shown in Fig 3(a). The image that is formed is shown in Fig 3(b), where the outer edge of the image corresponds to the high horizon shown in Fig 3(a), and the inner circle corresponds to the low horizon. The ODVS shown in Fig 3(a) has been developed by us for various applications, including different experiments in multiagent robot systems (e.g., see [1]. We have developed different prototype omni-directional vision sensors while investigating the properties of the captured images and the corresponding sensor parameters. Many of these prototypes were large, unwieldy, and their costs were high. Recently, we have developed small, compact, and low-cost ODVSs that are very robust for outdoor applications [5].



(a) Code phase GPS



(b) Carrier phase GPS

Figure 4: GPS system

2.1.2 Positioning System

In our application, we make use of carrier-phase differential GPS techniques for getting locations of obtained images.
In the case of building an image database of an outdoor environment, the positional accuracy is an important issue. Many ITS applications use GPS for positioning, particularly in conjunction with on-board navigational tools used for assisting drivers. However, the positional accuracy required for many of the navigational applications are on the order of 10 to 20 meters, which is achievable through the use of standard, low-cost, single frequency GPS receivers. Other ITS applications require higher positional accuracy of around 1 to 2 meters, which is achievable using differential GPS techniques. In this situation, known errors recorded from a base station are also sent to the mobile receiver, allowing the mobile unit to "subtract" the errors, achieving the higher accuracy. In our application where we use location as the index for the outdoor omni-directional image database, positional accuracy on the centimeter level is required. This is achievable if the GPS carrier signal is also used in the positioning equation.

The GPS satellites transmit bi-phase encoded signals at two frequencies denoted as L1 (1.575GHz) and L2 (1.227GHz). Two basic codes are written on the GPS carrier signals. In car navigation systems, code-phase GPS techniques are generally used. This technique obtains location data by measuring differences between satellite's pseudo random code and the receiver's pseudo random code as shown in Fig 4(a). When the carrier phase of the GPS signal is used (see Fig 4(b), higher positional accuracy can be achieved.

In our system setup, we obtain positional accuracy typically around 2cm. The GPS receiver estimates the position every one second. It is important to synchronize the image captures with the GPS data, particularly when the vehicle is moving at high speed. In our system, we use a pulse from the GPS receiver to trigger an image capture by the vision frame grabber.

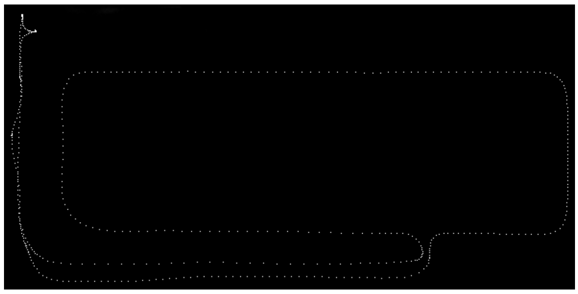


Figure 5: Position information from GPS

As an example, Fig. 5 shows the position information acquired from our instrumented vehicle as it moves in a large parking lot. The white points in this figure show the positions of the vehicle. The vehicle is simply following the periphery of the parking lot (approximately 200m x 400m in size). Traveling at a slow rate of speed, approximately 700 points were acquired in this example.

2.2 Display System

Once a large image database is acquired along with the position indices, it is necessary is store this large amount of data and be able to display various views at a high rate of speed. A display system was developed consisting of a dual processor PC outfitted with a 40 gigabyte RAID system. Various algorithms were developed that manipulated the database; some of these algorithms are described in Section 3. Some of the example applications that are capable with the display system include:

1. a 3-D navigation system
2. a virtual drive-through system
3. 3D modeling of the town
4. a driving training system, and
5. a surveillance system.

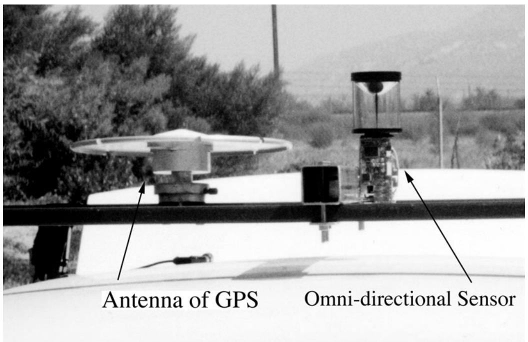


Figure 6: GPS & Omni-directional Vision Sensor on the Instrumented Vehicle

3 Experimental Results

3.1 Experiment in the Outdoors

In order to investigate the feasibility establishing a 3-D environmental model, approximately 6000 omni-directional images were acquired on the road system centered around the University of California, Riverside campus. This area spans approximately 50 square kilometers. Also contained in this area is the off-campus research laboratory where this research took place. The major roadways in this environment are illustrated in Fig. 7. Even though only the major roads are shown here, many of the other minor roadways were also included in the overall image database.

The instrumented vehicle equipped with the ODVS and GPS equipment (see Fig. 6) traversed all of the roads in the area several times. In Fig. 6, the left side shows the antenna of the GPS receiver and the right side shows the omni-directional vision sensor mounted on the roof of the vehicle. An example course on the major roadways is shown in Fig. 7. For this example course, the total distance the vehicle traveled was approximately 10km, requiring approximately 20 minutes to complete the course.

3.2 Drive-through System

Once the database was acquired, we wanted to be able to create a "drive-through" system where a user could arbitrarily choose any path in the environment. The display system would then simulate what the drive would look like, given any view direction along the simulated trip. Several functions were created, including a shortest path algorithm and a functional display system.

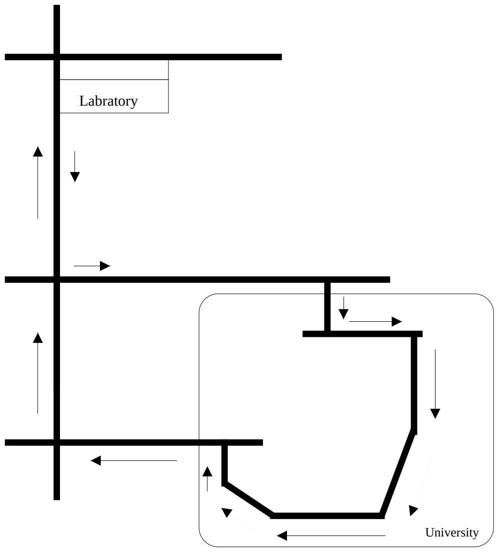


Figure 7: Major Roadways in Experimental Environment

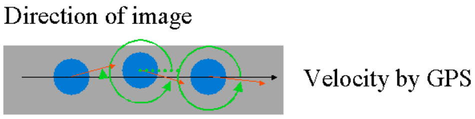
3.2.1 Finding the Shortest Path between Arbitrary Points

Using the graphical user interface, a user can simply click his mouse on the map of the area, and the nearest corresponding omni-directional image would appear. Another important feature is that the user can specify a starting and ending point anywhere on the map. Using the standard Dykstra algorithm, the system would determine the shortest (distance and/or time) path between the points, traveling on the roadways. Our roadway database also contains average travel times indexed by roadway link, so shortest-time routes can also be determined.

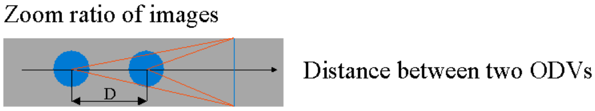
3.2.2 Display Function

The display for the drive-through system is shown in Fig. 9. The upper left portion of the display shows the acquired omni-directional image as a simulated route is being illustrated in real-time. The upper right portion of the display shows the standard perspective image, given any arbitrary viewing direction. This perspective view is created by warping the omni-directional image appropriately (this is done with high realism when a hyperbolic-shaped mirror is used in the ODVS). The lower right portion of the display shows the overhead map of the roadways and where the simulated vehicle is at any point in time. The lower left portion of the display shows a zoomed in version of the map at the point of the simulated vehicle.

Simply using the mouse on the display, the user can



(a) Direction of image



(b) Zoom ratio

Figure 8: Front View

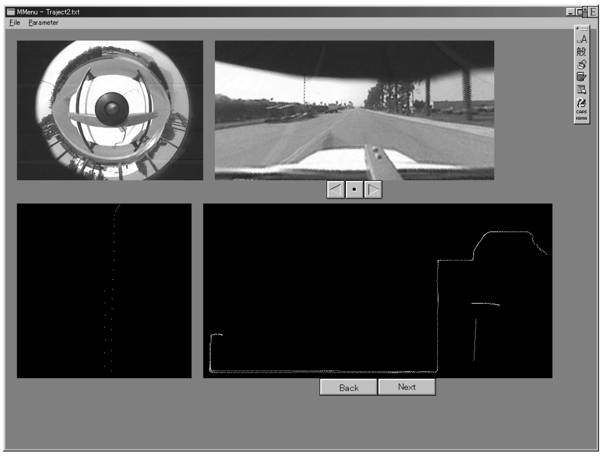


Figure 9: Walk-through system

designate the moving direction as well as the viewing direction on the map. For the best realism, the perspective image must change smoothly. This is accomplished by computing two key parameters. One is the direction of images along the calculated route. This direction is computed from the GPS-based velocity as shown in Fig. 8 (a). The other parameter is a zoom ratio between any two subsequent images, as shown in Fig. 8 (b). This parameter is computed from the physical distance between two images (remember that each image is indexed by an accurate position measurement).

Fig. 10 shows an example of a drive-through image sequence using this method.

3.3 Building a 3D Environmental Model

One of the key features of using position-indexed omni-directional views is that it is possible to deter-

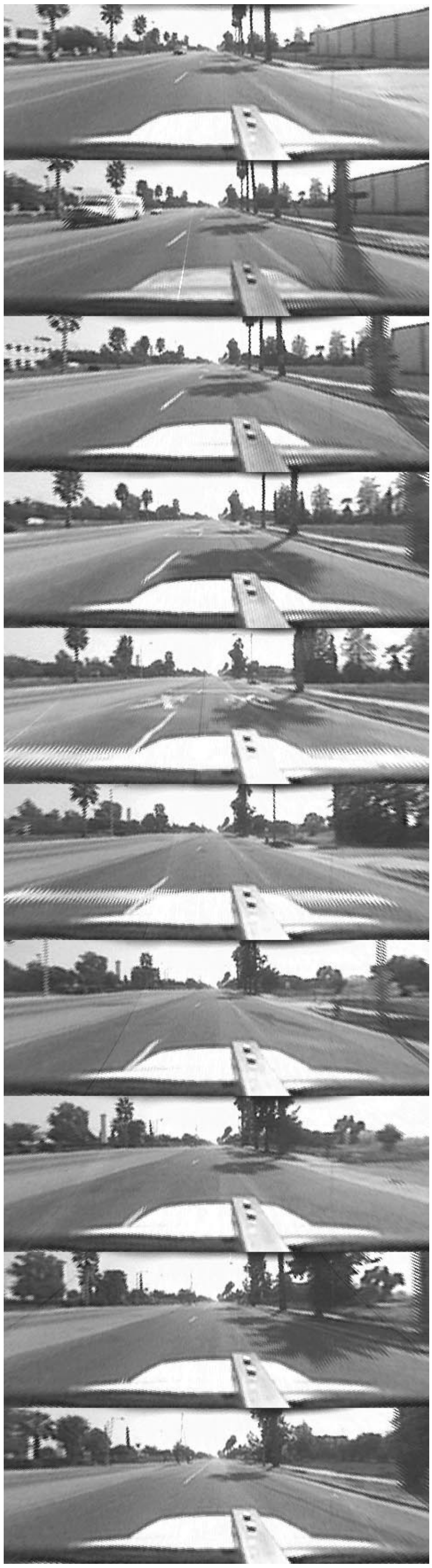


Figure 10: Image sequence taken by ODVS

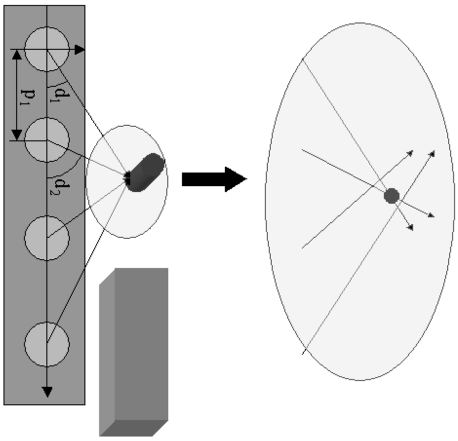


Figure 11: Multiple baseline stereo

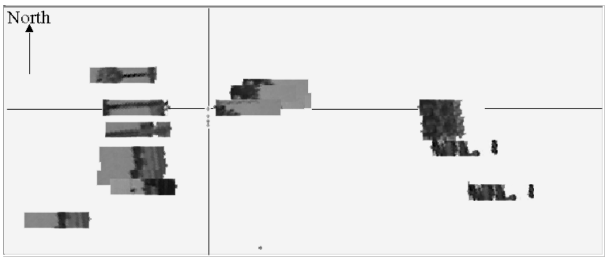


Figure 12: Experimental result

mine distances to different features in the environment. This is accomplished by using a standard multiple baseline stereo technique. In short, the different omni-directional images in a region will have established baselines between them; these baselines can be exploited when similar image features are found in the different images. In our application, the omni-directional images are dense, and common features are identified using a pattern matching method. The multiple baseline stereo method for detecting accurate locations of the objects is shown in Fig. 11. Initially, distances to features are found between neighboring image pairs. These features are then located in subsequent images, relating the features back to images taken at greater baselines.

Fig. 12 shows example results of this technique, using four omni-directional images. In this figure, the features are shown at the approximate calculated distance from the vehicle path shown by the vertical line.

4 Conclusions

In this paper, we describe a method for rapidly building an image-based environmental model that can be used for different ITS tasks. In the developed system, the data acquisition methodology is quite simple. The resulting database can be manipulated in a number of ways for different tasks. Thus far, we have developed a virtual drive-through system that can be used to preview particular routes in a roadway network. Further, we are currently integrating this image database with an on-board vehicle navigation system to provide driver assistance while driving in an unknown environment. Other techniques will be developed in the future, such as focusing on roadway surveillance applications.

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