

Real-Time Vision for Unmanned Vehicles

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ABSTRACT

This paper provides examples of how real-time vision may be used for controlling both teleoperated and autonomous vehicles. For teleoperated vehicles, we describe a system for video compression for low data rate remote vehicle driving. For autonomous vehicles, we describe passive range extraction from optical flow for applications such as target extraction and identification, vehicle driving, and terrain mapping.

1. Introduction

Unmanned vehicles are typically divided into two types, autonomous and teleoperated. However, it is often more convenient to think in terms of degrees of autonomy. A vehicle where the remote operator has direct control of the motor or actuator drivers, i.e., control of the individual thruster drive currents, would be the least autonomous. On the other hand, a vehicle that has independent control of its own mission definition, or that could alter strategy and mission priorities, would be the most autonomous.

A control system architecture that unifies autonomous and teleoperated control is the National Institute of Standards and Technology (NIST) Real-time Control System (RCS) architecture [1, 2, 4, 7, 17]. The system is a three legged, multi-level hierarchy of computing modules for task decomposition, world modeling, and sensory processing. This hierarchy is serviced by a communications system and a distributed common memory, and is interfaced to operator and programmer workstations. The architecture supports both teleoperated and autonomous control.

This paper first describes the NIST Control System Architecture. It then focuses on recent work at NIST in real-time vision for both teleoperated and autonomous vehicles. For teleoperated vehicles, we describe a system for video compression for low data rate remote vehicle driving. For autonomous vehicles, we describe passive range extraction from optical flow for applications such as target extraction and identification, vehicle driving, and terrain mapping.

2. Real-Time Control System Architecture

In the NIST Control System Architecture (Figure 1), the task decomposition hierarchy decomposes long range goals into drive signals to actuators. Task goals are decomposed both spatially and temporally. Task decomposition is accomplished by performing real-time planning, execution, and task monitoring.

The sensory processing hierarchy interprets the world at multiple levels of abstraction. This is accomplished by filtering, correlating and integrating sensory information over both space and time so as to detect, recognize and measure patterns, features, objects, events, and relationships in the external world.

The world model hierarchy serves as an interface between the sensory processing and task decomposition hierarchies. The world modeling modules answer queries, make predictions, and compute evaluation functions on the state space defined by the information stored in global memory. Each level in the task decomposition hierarchy may access a number of different levels in the world model hierarchy. The global memory is a database which contains the system's best estimate of the state of the external world. The world modeling modules keep the global memory database current and consistent.

Operator interfaces allow operator access to any level of the hierarchy.

3. Video Compression for Remote Vehicle Driving

Remotely driving a ground vehicle involves an operator who sits at a remote control center and views video images that are transmitted from one or more cameras mounted on the vehicle. While observing these images, the operator drives the vehicle by means of driving controls involving steering, brakes, throttle, and transmission. These controls generate appropriate driving actuator signals which are transmitted to the vehicle.

In order for the operator to effectively drive the vehicle, the video images must be of sufficient quality and must be updated as frequently as possible. Full rate video transmission from the vehicle to the operator requires about 60 megabits per second for 512 x 512 images with 8 bits per pixel at 30 frames per second. However there are several problems with using the wide communication bandwidth required for such transmission. First, wide bandwidth radio communication requires direct line of sight between the transmitter and receiver. This is not feasible in realistic outdoor scenarios where vehicles are likely to be driven behind hills and mountains and therefore hidden from direct view by the operator station. Second, wide bandwidth links are relatively expensive. Finally, full rate video uses up a large part of the bandwidth allocations. This could present a problem if there are many vehicles being operated simultaneously, since wide bandwidth links for the vehicles could combine to exceed the entire communication spectrum. Fiber optic tethers, which have wide bandwidth communications capabilities, also have several problems, including limited ruggedness, difficulties in deployment and retrieval, and the problem of repairs.

Many of these difficulties can be overcome by utilizing narrow band radio links which have communication bandwidths on the order of 100 kilobits per second or less. Since the full video desired for teleoperation cannot be transmitted over narrow band links, efficient and effective techniques of real-time video compression offering compression ratios of 500:1 to 1000:1 must be developed.

3.1. Approach

To solve the problem of video compression for remote driving, we have proposed a hybrid method which combines image processing compression (i.e., techniques whose input is an image and whose output is a compressed image), discrete cosine transform compression,

and temporal frame rate reduction (i.e., transmitting much less than 30 frames per second). The sequence of events as they would occur in the system is as follows. Images are obtained from one or more cameras mounted on-board the vehicle. These images then undergo compression using the hybrid technique. After the compressed code is transmitted over a communication link to the operator station, it is decompressed so as to result in a sequence of full resolution images.

Several algorithms for the image processing compression portion of this method have been implemented to run in real time on the PIPE image processing machine [11] and have been used in actual field experiments for teleoperated control. The algorithms implemented on PIPE include grey level quantization, non-maximal edge suppression, foveal-peripheral simulation, image differencing, histogram slicing, binning, Laplacian pyramid decomposition and reconstruction, decimation and Poisson interpolation, and linear predictive coding. Details describing these algorithms and their implementation on PIPE are presented in [8].

Several of the compression algorithms running on PIPE were tested during real-world remote driving experiments. PIPE was set up at the remote operator station, using as input video returning from the vehicle. PIPE then performed real-time video compression on the input images, and the results were displayed on the monitor and used by the operator to drive the vehicle. Experiments were performed in a paved loading dock area surrounded by buildings, on an uneven grassy field, and on a dirt field on which obstacles were placed. The main difficulties that were encountered during the experiments, particularly when driving in open terrain, were

1. global vehicle location relative to the background and landmarks was very difficult to determine,
2. the slope of the local terrain was very difficult to determine,
3. ditches, gullies, rocks, and other obstacles were difficult to distinguish,
4. range from the vehicle to objects and terrain features were difficult to determine.

Object and terrain feature segmentation was very difficult in monochrome images. This was particularly true in the open field where the main way of discriminating between objects and the field was by color -- the field was covered with green grass and weeds, while objects and obstacles were brown, silver, or red. Further details on the results of these experiments are described in [9].

From these experiments, we have concluded that the critical element in achieving teleoperated driving control is to minimize the degradation of the imagery transmitted to the operator. Unfortunately, most compression techniques that achieve significant compression ratios result in significantly degraded imagery. In order to limit the degradation, we propose a technique involving the use of simulation to achieve real-time compression. The idea here is to transmit imagery at a very low frame rate (perhaps only a few times per second or once every few seconds), and to have a realistic simulation at the operator station which simulates the intermediate imagery that would appear in the vehicle camera. In order to achieve realistic simulation, both an accurate scene model and accurate navigation data (position, velocity, and acceleration of the vehicle) are required.

3.2. Video Compression Using Simulation

The technique of video compression using simulation involves transmitting an image (called the *master* image) relatively infrequently (perhaps once every few seconds), but then warping the master image in real time to generate a sequence of simulated images for the operator [14]. These images are meant to approximate those that would appear in the camera on the vehicle. When a new image arrives from the vehicle, it becomes the new master image

and the procedure is repeated.

The basic concept is shown in Figure 2. Let c_0 be the pose of the camera when the master image is taken, and let c_i be the pose of the camera at some future point at which we want to generate a simulated image. For some pixel p_0 in the c_0 image, we know that the point P_s in the scene corresponding to this pixel lies along a ray from the camera focal point through the pixel p_0 out into the scene. In fact, the point P_s is at the intersection of this ray with the first surface it meets. If we know the position of this surface from a scene model, then we can determine P_s . We propose to use real-time passive ranging from optical flow to dynamically generate such a model. The pixel p_i in c_i corresponding to pixel p_0 in c_0 is simply obtained by the intersection of the line containing P_s and the focal point of c_i with the image plane of c_i . Pixel p_i will then be given the same grey level value as pixel p_0 . In practice, the point p_0 corresponding to pixel p_i will lie in between pixels. Therefore, the grey value assigned to pixel p_i will be obtained by interpolating pixel values in a small neighborhood around p_0 . When this procedure is carried out for every pixel in c_i , we have the resulting warped image.

Briefly, the operation of such a system is as follows. Range images are continuously computed on-board the remote vehicle using optical flow. Every 3 seconds, both a range and a video image are transmitted from the remote vehicle to the operator station. Time-tagged vehicle navigation data are transmitted from the vehicle continuously at 30 Hz. These navigation data are used to estimate the position and orientation of the camera in the scene during the simulated views. Simulated images are then generated at 30 Hz from the master image, range data, and navigation data. These images are displayed to the operator and provide the approximate current vehicle scene. Because the vehicle's pose is always known to a high accuracy, all vehicle motions can be reflected instantly in the operator display. A Kalman filter is applied to the navigation data so that a smooth extrapolation is obtained to the point in time at which the image is to be displayed at 30 Hz.

4. Real-Time Passive Ranging Using Optical Flow

Optical flow is the flow of intensity information across the image plane due to relative motion between the camera and objects in the environment. It may be represented in the form of an image, where each pixel has associated with it an instantaneous velocity vector representing image motion at that point. In practice, optical flow is extracted by processing a time sequence of at least two images. The goal of our work in this area has been to extract highly accurate optical flow in real time. This can be done if the flow direction at every point is known ahead of time.

4.1. Predicting the Flow Field

Our method of passive ranging assumes that (a) the camera is moving in a stationary world and (b) the camera motion is known. These assumptions lead to two conclusions. First, the optical flow field in the image (i.e., the flow direction at every point) can be predicted. Second, once optical flow has been extracted, the flow vectors can easily be converted to range values. To see why, we will consider three types of camera motion -- pure translation, pure rotation, and a combination of translation and rotation.

Consider a camera undergoing pure translation. Figure 3 is an illustration from Gibson [6] showing the optical flow induced by this motion in a stationary environment. The arrows represent angular velocities of flow vectors formed by spherical projection of the environment onto a sphere centered at the camera focal point. Note that the flow vectors are zero directly ahead of and behind the moving object. The point directly ahead is called the *focus of expansion* (FOE), and all points appear to flow outward from this point. All flow vectors lie along great circles on the sphere as shown in the figure. If a camera with a planar imaging element

were located at the center of the sphere, then the great circles, when centrally projected into the camera, would appear as straight lines in the image plane. Furthermore, if the FOE were also projected into the camera, then all motion would appear to flow radially outward in straight lines from this point. Therefore, if the camera motion is known, the flow direction at each image point can be predicted.

To see how the flow vectors can be converted into range values, consider the spherical coordinate system shown in Figure 4. A point P in the scene is projected onto the sphere by intersecting the ray from the camera focal point to P with the surface of the sphere. In Figure 4, suppose that the positive y -axis is defined by the camera velocity vector. Then the set of great circles that intersect the y -axis represent optical flow lines. Consider a point of interest P' on the sphere. Let A be the angle from the positive y -axis to the ray from the camera center to P' and let B be the angle from the positive z -axis to the plane of the great circle containing P' . If v is the camera velocity and dA/dt is the value of the optical flow on the sphere at angle A , then the following formula is used to calculate the range r to the point in the scene corresponding to the point at A [3]:

$$r = \frac{v \sin A}{dA/dt}. \quad (1)$$

For a camera undergoing pure rotation, all optical flow on the sphere will be along small circles perpendicular to the axis of rotation. For known camera motion, not only the flow direction but also the flow magnitude at each image point can be predicted. However, camera rotation provides no information for calculating range.

For a camera undergoing both rotation and translation, the optical flow at each image point is given by the vector sum of the rotational and translational components of flow. Figure 5 shows the situation where the translation vector is perpendicular to the rotational axis. At point P' on the sphere, the direction and magnitude of optical flow due to the known rotation can be predicted along the small circle as shown. The direction of flow due to the known translation can be predicted along the great circle as shown. Since the magnitude of the flow vector due to translation cannot be predicted from the camera motion, the resultant flow vector at point P' lies within a family of vectors as shown in the figure. One technique that can be used to extract and analyze the optical flow is to subtract out the flow due to rotation. This can be accomplished by warping each image so as to eliminate all grey scale displacements due to rotation. This is easily accomplished for known camera rotation. The result is a temporal sequence of images with no rotational flow components. For these images, the flow direction can be predicted, extracted, and converted to range values as described above for pure translational motion.

4.2. Accuracy and Real-Time Performance

The methods described above show how the flow field can be predicted. In this section, we describe how knowledge of this flow field can lead to extraction of highly accurate optical flow and to real-time performance.

First, when extracting the flow vectors, knowledge of the vector directions eliminates the aperture problem [12]. The aperture problem states that if image motion is detected using a spatially local operator, then only the component of motion parallel to the local brightness gradient can be computed. This component of motion is called normal flow. Typically, this problem is handled with a costly constraint satisfaction algorithm that combines the normal flow components over an extended region of the image. Because our approach assumes that the flow vector directions are already known, only the magnitudes of the flow vectors need to be computed. This leads to real-time performance. Another factor leading to real-time

performance is that by eliminating the aperture problem, local image operators can be used to extract the flow, and these local operators can run in parallel. Our approach should also lead to greater accuracy of extracted flow vectors since we already know the vector direction accurately.

Knowledge of the motion field also allows the use of temporal consistency to increase accuracy. Temporal consistency means that flow vectors should remain consistent over time. Suppose the camera is in two successive positions due to its motion over a short distance. Then for almost every point in the first image, there will be a point in the second image that corresponds to the same 3-D point in the scene. Corresponding points are assumed to have consistent flow values because they arise from the same point in the scene. The assumption of temporal consistency is that flow values for corresponding points change only as a function of geometry, i.e., as a function of the relative positions of the moving camera and as a function of the camera's speed. We utilize temporal consistency as follows. First calculate the flow values at each pixel for multiple image frames spanning a short period of time. Then determine corresponding points in the multiple images. Correspondences can be determined from the computed flow values since these values are proportional to pixel disparities. We then normalize these flow values to eliminate differences in geometry. Next, the resulting flow values are integrated over the multiple images. This should result in improved estimates of the flow values [13]. We have implemented this algorithm on PIPE by doing the integration using running averaging over about 10 image frames. A slightly different version of this algorithm which first converts flow values to range values and then integrates these values in a world coordinate system has been implemented on the Sun-3 computer (see [3] for details).

4.3. Flow Extraction Techniques

This section describes three optical flow extraction techniques that we have implemented for our experiments. These are (1) spatial and temporal derivatives, (2) spatio-temporal imagery and (3) temporal cross correlation. The technique of spatial and temporal derivatives is based on a method developed by Horn and Schunk [10] which involves calculating both spatial and temporal derivatives at each point in the image. Because a spatially local image operator is involved, this method normally computes only the flow component parallel to the spatial gradient. However we make use of the known flow direction to compute the true flow as the ratio of the temporal derivative to the directional spatial derivative along the flow line. This technique has been implemented on PIPE and is described in more detail in [16].

Another technique we have implemented is the method of spatio-temporal image analysis (or epipolar-plane image analysis [5]). Suppose that the camera is moving in the horizontal direction, along its scan lines, and consider scan line j in the image. We can associate a spatio-temporal image with this scan line in which the x-axis represents the x-direction along the scan line and the y-axis represents time. Each row of the spatio-temporal image will show the given scan line at a different point in time. Each feature on the original scan line will generate a line, or *streak*, in the spatio-temporal image. The slope of the streak is proportional to the optical flow of the feature; the smaller the slope, the greater the flow velocity. This algorithm has been implemented to run in real time on PIPE. We have also implemented edge finding techniques to extract the slope of the streaks. The resulting slope images are thresholded to perform range segmentation. Further details are provided in [15].

Another technique that we have implemented is temporal cross correlation. This method involves obtaining the temporal brightness profile (i.e., intensity vs. time) for pairs of pixels. These pixels may be adjacent to one another or may be separated by some distance. By correlating these profiles, we can determine the amount of time for brightness values to travel from one pixel to the next.

4.4. Using Optical Flow for Unmanned Vehicles

In order to use optical flow for unmanned vehicles, we classify the flow into two categories: (1) the global flow field induced by vehicle and camera motion, and (2) the local flow fields induced by motion of objects in the environment. The flow due to the first category is useful for vehicle driving, for 3-D terrain reconstruction, for acquiring stationary targets, and for 3-D landmark recognition. The flow due to the second category is useful for acquiring, identifying, and tracking moving targets or objects. To make use of the global flow field, we need an inertial navigation system that gives us vehicle and camera motion. Once we know the camera motion, we can subtract out the rotation of the camera (as described above) and calculate the FOE accurately. This allows accurate and real-time extraction of the global flow field. To make all of this work in real time, the camera should be stabilized so that optical flow due to camera jitter is eliminated.

5. Integration of Teleoperation and Autonomy

The various techniques for vision-based teleoperated and autonomous driving discussed above can be unified under the NIST hierarchical control system architecture, resulting in a single integrated system (Figure 6). In such a system, compressed imagery from the vehicle camera and range images computed from optical flow are transmitted periodically to the operator station. Navigation data are transmitted very frequently. Through simulation, continuous video is displayed on the operator's console. As he monitors the video, he may enter commands into the control system at any level he desires. Normally, he will enter vehicle task commands and monitor their autonomous execution. If he wants a finer level of control, he will enter intermediate key poses. If the system does not seem to be executing the desired actions, or if a delicate situation is at hand, the operator will want to be able to enter the control system either by indicating safe motion pathways or by specifying dynamically efficient trajectories (i.e., directly controlling steering, brakes, throttle, and transmission). The control system will allow the operator to impose his own commands at any level of the hierarchy and at different levels as the situation requires.

6. Conclusion

Vision is very important for controlling both autonomous and teleoperated unmanned vehicles, particularly in outdoor environments. This paper has presented real-time vision systems for low data rate remote driving and for passive range extraction. The paper has also shown how a single integrated system can be developed. Such a system would allow the operator to visually monitor execution of commands by the vehicle and to enter commands into the control hierarchy at any level he desires. Such a system would also allow powerful vision techniques such as optical flow to be used in varied control situations.

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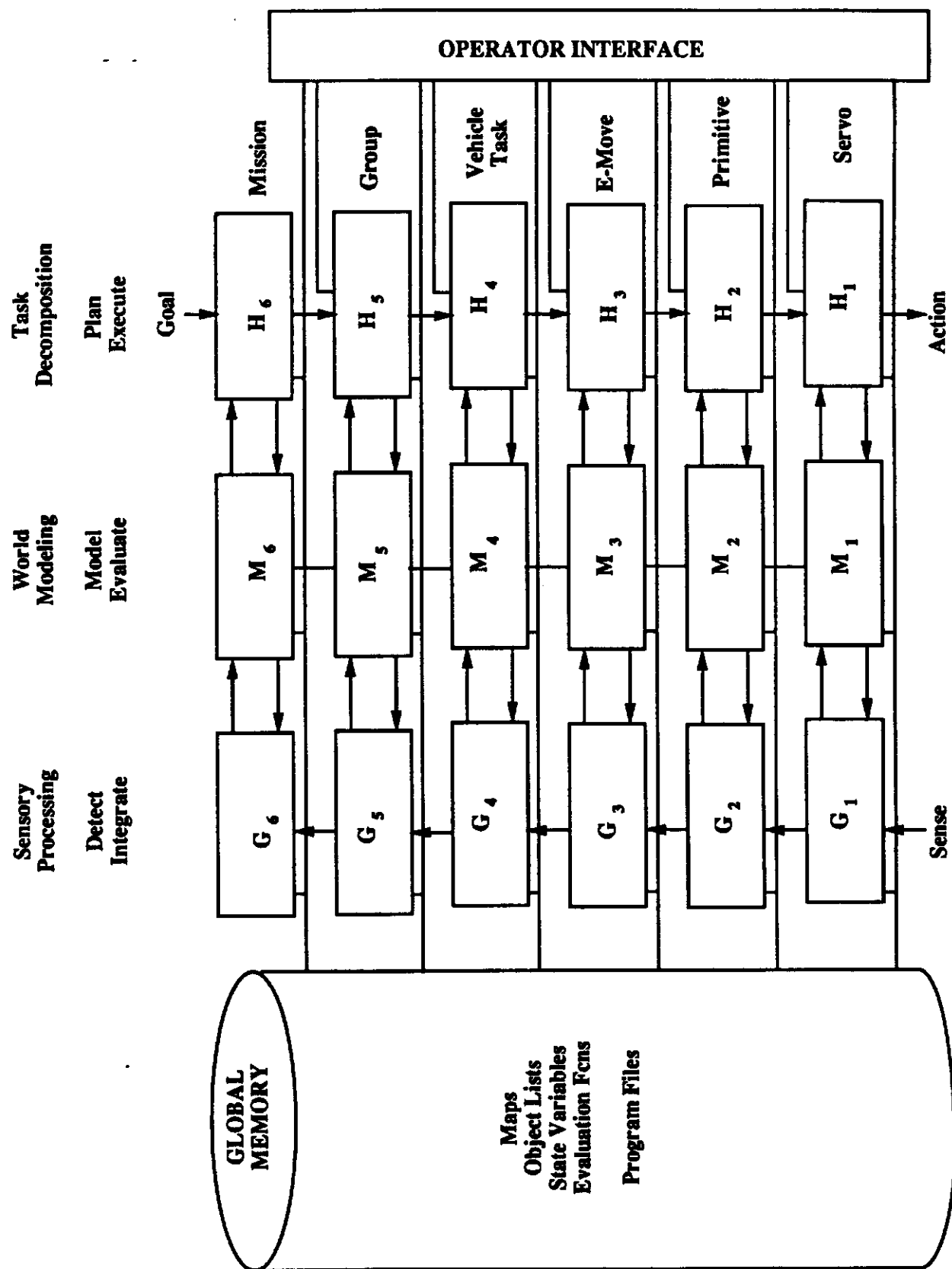


Figure 1. Real-time control system architecture for unmanned vehicles.

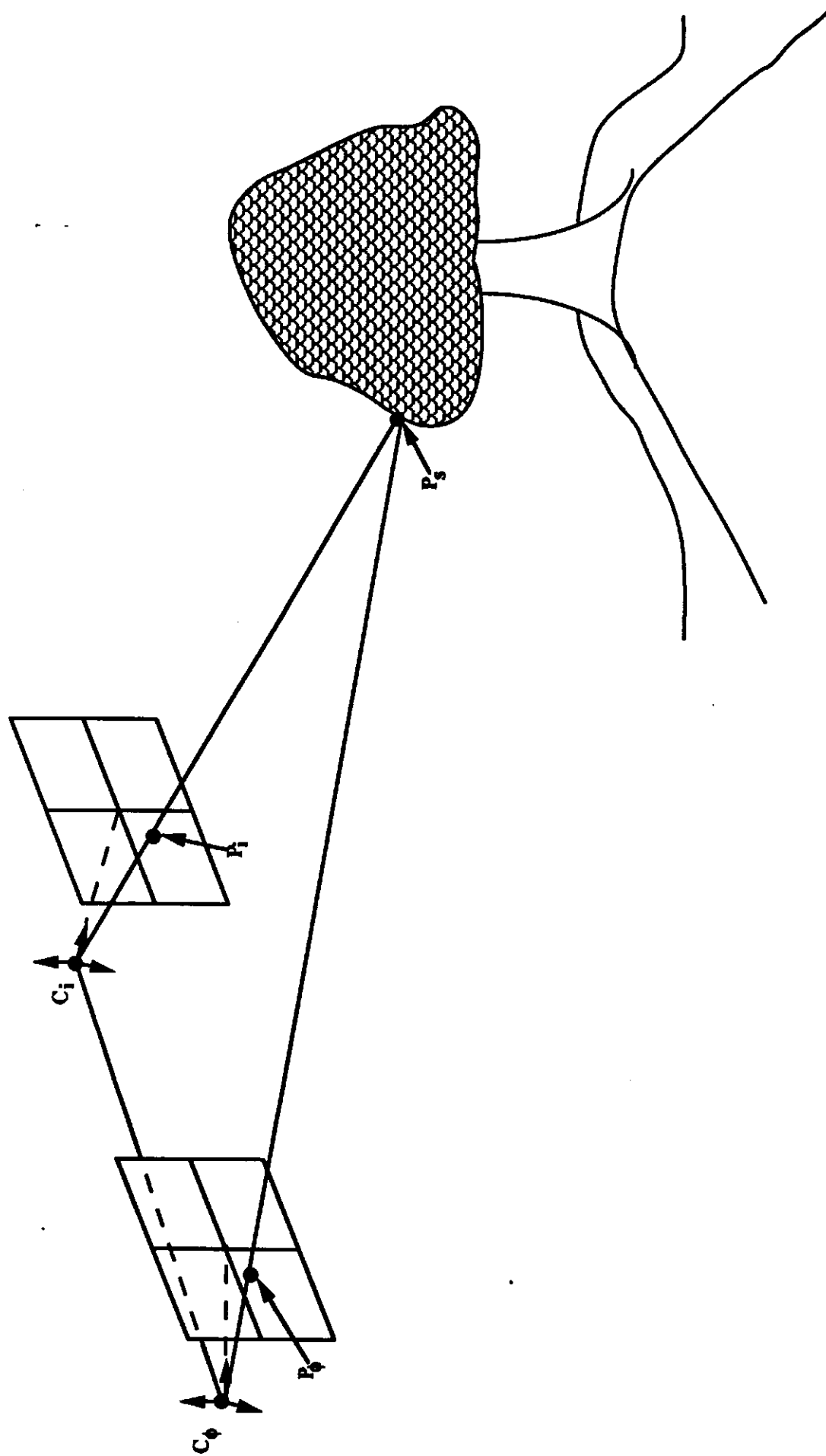


Figure 2. Geometry for generating simulated imagery.

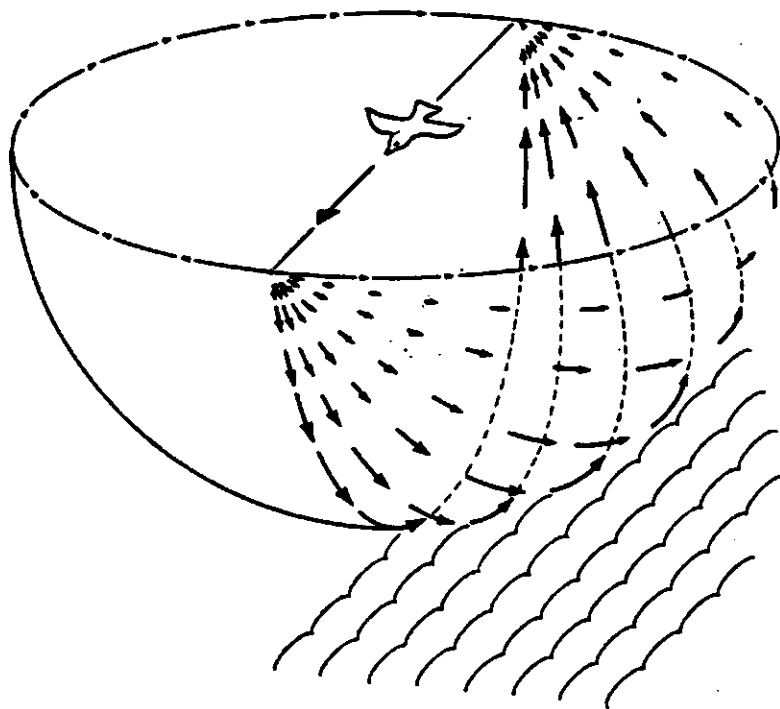


Figure 3. Optical flow induced by camera motion. (Reprinted from Gibson [6], fig. 9.3)

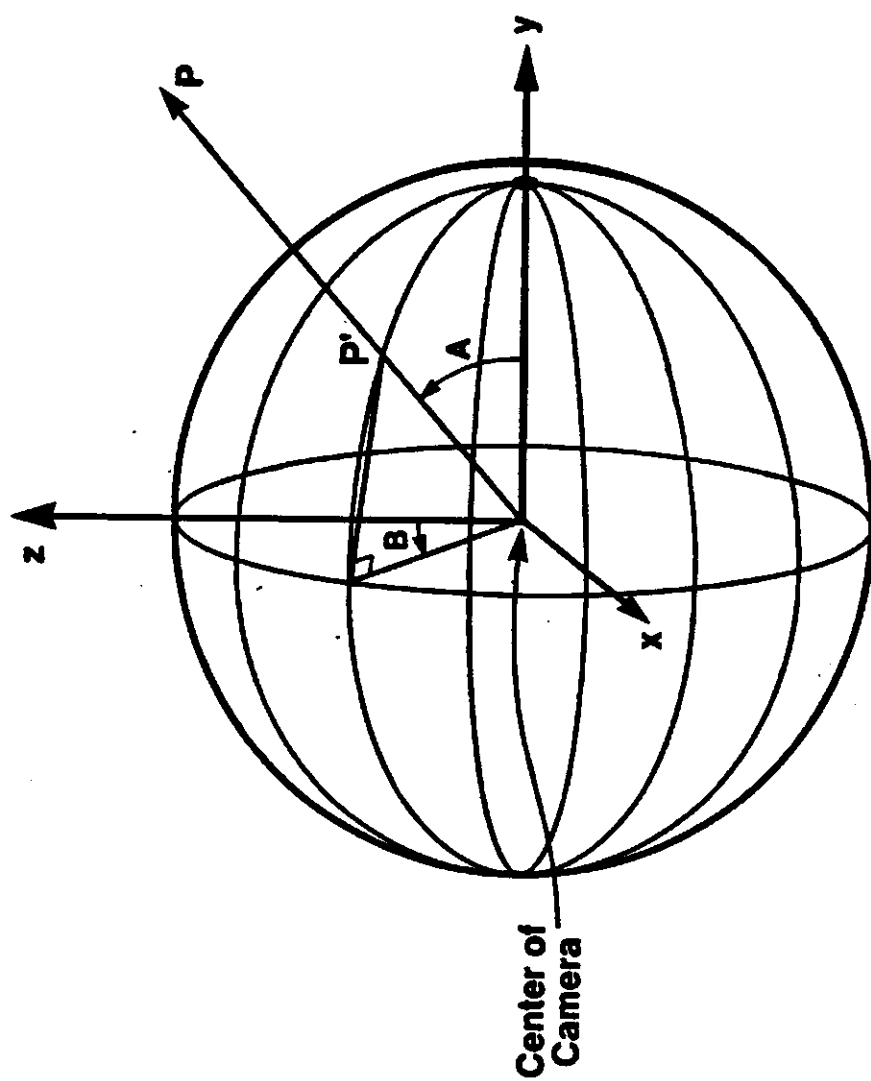


Figure 4. Spherical coordinate system for optical flow.

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OPTIC FLOW DUE TO COMBINED ROTATION AND TRANSLATION

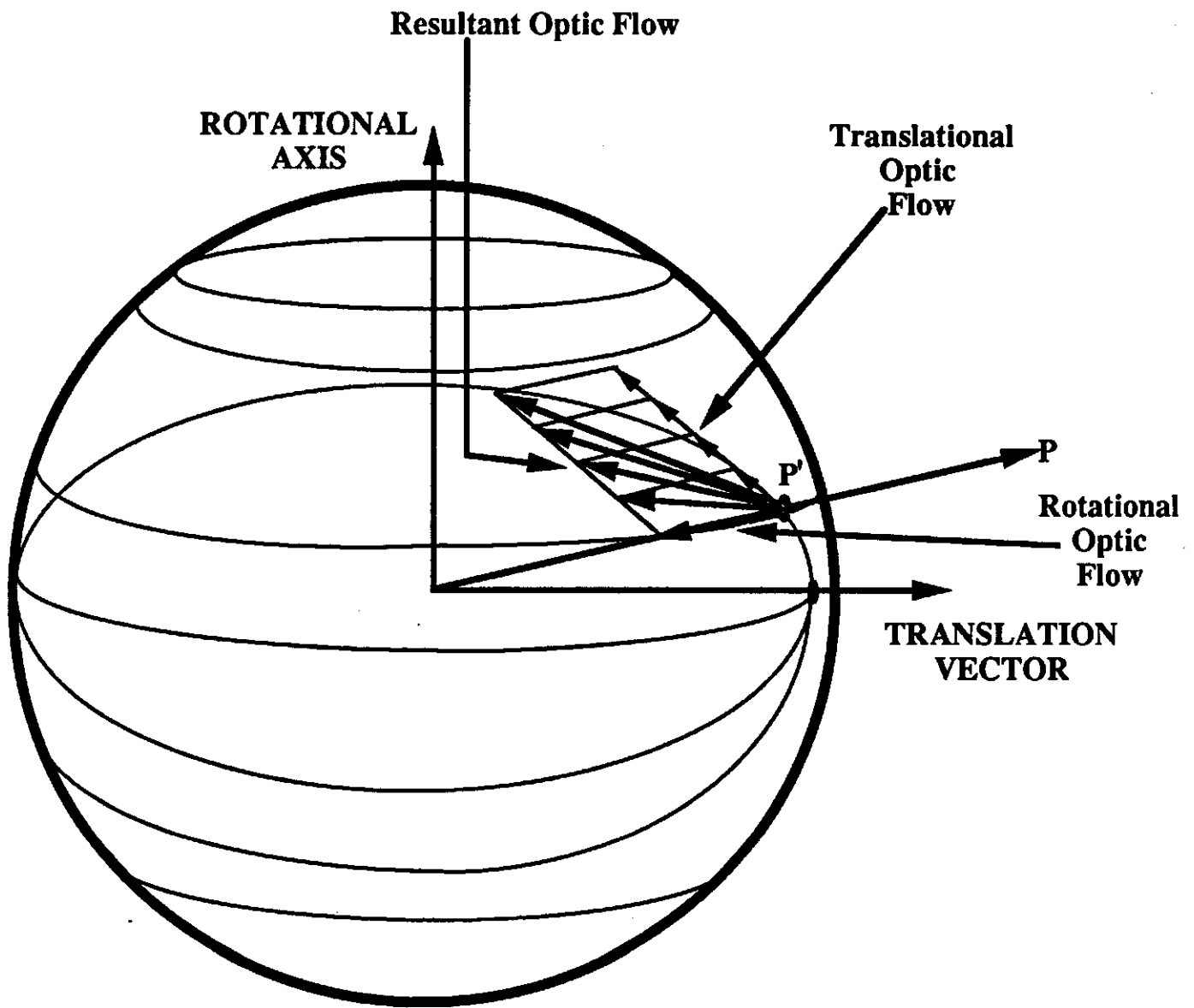
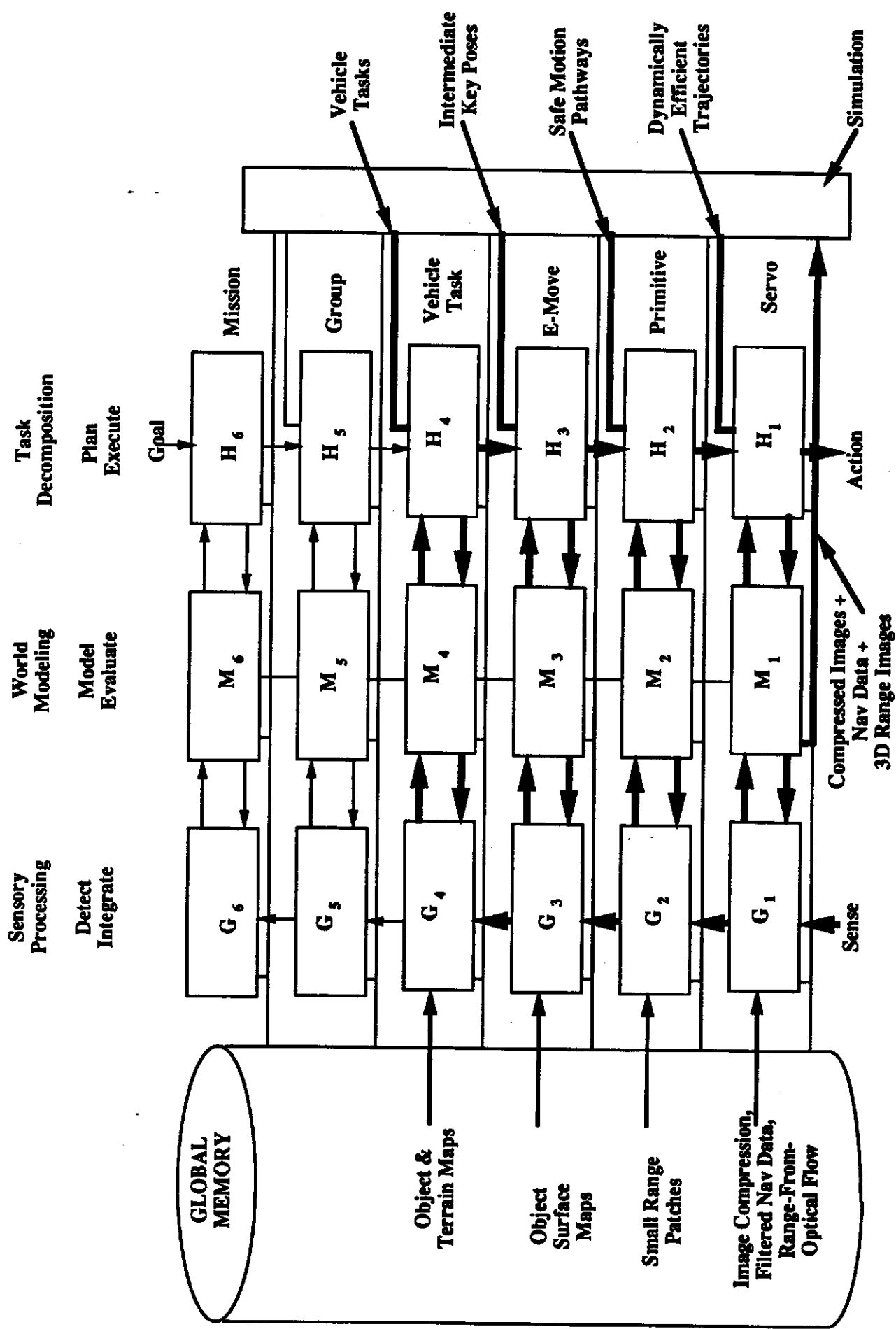


Figure 5.



INTEGRATED TELEOPERATED AND AUTONOMOUS DRIVING

Figure 6. Thick lines indicate relevant communication pathways.