The Role of Multisensor Integration and Fusion in the Operation of Mobile Robots

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Abstract—The use of multisensor integration and fusion enables a multisensor-based mobile robot to operate in uncertain or unknown dynamic environments. After first distinguishing between multisensor integration and the more restricted notion of multisensor fusion, the role of multisensor integration and fusion in the operation a mobile robot is described with reference to the type of information that the integrated multiple sensors can uniquely provide the robot. A hypothetical mobile robot architecture is used to illustrate the generic functions necessary for intelligent autonomous mobility. A variety of proposed high-level representations for multisensory information are presented, along with a discussion of different sensor combinations that have been used in mobile robots. The paper concludes with short descriptions of a selection of different mobile robots to illustrate the role of multisensor integration and fusion in their operation.

I. INTRODUCTION

THE MOBILITY of robots and other vehicles is required in a variety of applications. In simple well-structured environments, automatic control technology together with simple sensory processing may be sufficient to coordinate the operation of a mobile robot (e.g., automatic guided vehicles, etc.). When a robot must operate autonomously in an uncertain or unknown dynamic environment—usually in close to real-time—it becomes necessary to consider integrating or fusing the data from a variety of different sensors so that an adequate amount of information from the environment can be quickly perceived. Because of these factors, multisensor-based mobile robot research has proved to be a major stimulus to the development of concrete approaches to multisensor integration and fusion.

While in many multisensor systems the information from each sensor serves as a separate input to the system, the unique aspects involved in the actual combination or fusion of information prior to its use in the system has made it useful to distinguish between multisensor integration and multisensor fusion [1]. Multisensor integration refers to the synergistic use of the information provided by multiple sensory devices to control the operation of an intelligent system. Multisensor fusion refers to any stage in the integration process where there is an actual combination (or fusion) into one representational format of different sources of sensory information or information from a single sensory device acquired over an extended time period. The distinction of fusion from integration serves to separate the more general issues involved in the integration of multiple sensory devices at the system architecture and control level, from the more specific issues (e.g., mathematical or statistical) involving the actual fusion of sensory information—e.g., in many multisensor-based mobile robots the information from one sensor may be used to guide the operation of other sensors on the robot without ever actually fusing the sensors' information.

The need for an effective method of integrating multisensory information was recognized during the development of the first mobile robots. In addition to robotic research, multisensor integration and fusion has since become a topic of research in computer vision, artificial intelligence, pattern recognition, neural networks, statistics, and automatic control; and an important aspect in the development of a number of intelligent systems in areas of application including material handling, assembly, military command and control, target tracking, and aircraft navigation. Common among all of these applications is the requirement that the system intelligently interact with and operate in an unstructured environment without the complete control of a human operator. Luo and Kay [1], [2] have discussed some of the multisensor integration and fusion issues and approaches common to all of these applications, and Levi [3] has described multisensor fusion techniques appropriate for mobile robot navigation and has reviewed their use in a number of existing robots.

II. THE ROLE OF MULTISENSOR INTEGRATION AND FUSION

The role of multisensor integration and fusion in the operation of a mobile robot can best be understood with reference to the type of information that the integrated multiple sensors can uniquely provide. The potential advantages gained through the synergistic use of multisensory information are that the information can be obtained more accurately, concerning features that are impossible to perceive with individual sensors, in less time, and at a lesser cost. These advantages correspond, respectively, to the notions of the redundancy, complementarity, timeliness, and cost of the information provided the robot. The role of multisensor integration and fusion can then be defined as the degree to which each of these four aspects is present in the information provided by the sensors.

Fig. 1 illustrates the role of the perception function in a hypothetical architecture for a multisensor-based mobile robot. Perception, together with vehicle control, obstacle avoidance, position location, path planning, and learning, are generic functions necessary for intelligent autonomous mobility [4]. Six different external sensor types are shown in the figure as part of the perception function. Subsets of these sensors are used to perform three tasks that usually comprise the perception function: the matching of sensory data to a world model (or map) representing the environment and then updating the model to reflect the matching results, the recognition of landmarks in the environment for use in determining the location of the robot, and the detection of obstacles so that they can be avoided. The degree of integration and fusion of the sensory data required for each of these tasks can differ. In a simple system, each sensor used for obstacle detection might operate independently of the other sensors if the detection of nearby obstacles is required. In a more complex system, some of the sensor data might be also fused so as to extend the range and accuracy of possible detection

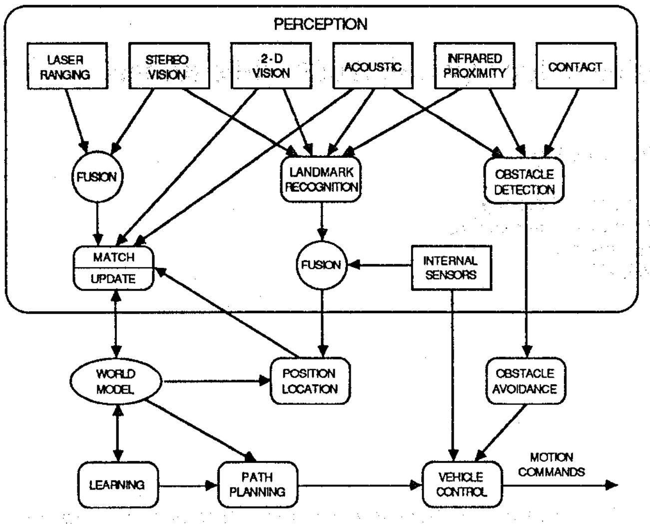

Fig. 1. The role of the perception function in a hypothetical architecture for a multisensor-based mobile robot.

[5]. One of the simplest techniques used for position location is trajectory integration, where the location is calculated from the accumulated rotational and translational motion of the vehicle as determined by internal sensors like an odometer. Due to the inherent inaccuracies in any sensor, locational error continues to accumulate as the robot moves. In order to deduce this cumulative error, most mobile robots periodically determine the location of some external landmark. As shown in the figure, the results from landmark recognition are sometimes fused with the location determined by internal sensors after each has been transformed to common coordinates. Many different methods of multisensor object recognition can be used to first recognize the landmark. The world model matching and updating task requires that the sensor information and any associated measure of its uncertainty correspond to the representation used in the world model so that integration can take place. Depending on the representational format used in the world model, the information will in most cases have to be made commensurate by applying appropriate space and time transformations. Information from the different sensors might be fused or otherwise transformed before reaching the matching task in order to reduce the communication bandwidth required or the complexity of the matching process. In the figure, information from the laser ranging and stereo vision sensors are fused before being matched to the world model.

While the hypothetical architecture described above represents in broad outline most current approaches to the design of mobile robots, the MIT mobile robot project has adopted a radically different layered approach for autonomous control that they term a "subsumption" architecture [6], [7]. Each layer in this architecture consists of a complete control system, similar to that in Fig. 1, for a simple task achieving behavior like avoiding obstacles or wandering. Starting with low-level tasks, new task achieving behaviors can be added incrementally because the layers operate asynchronously, communicating over low-bandwidth lines, without a central locus of control, central data structure, or global plan.

III. High-Level Representations

Considerable research has been directed at the development of either a single representation or multiple hierarchial levels of representations suitable for use by a multisensor-based mobile robot to perform the reasoning required for its control, path planning, and learning functions. The representations are usually at a high enough level so as not to be sensor specific. As mentioned above, information from different sensors is usually transformed to the common high-level representation and then added to a world model. The function of the world model and the particular form of the high-level representation depend both on the control architecture used in the robot and the complexity of the required reasoning—extremes range from road-following vehicles where sensor information is dynamically processed using feedback loops to produce control commands without ever using a world model, to pure production rule-based representations that assume a static and perfect model of the world that is difficult to modify [8]. In practice, the representations used for robots operating in unknown or unstructured environments allow for their world models to be dynamically modified and updated with uncertain sensor information. Except for explicit learning procedures used in many production rule-based representations, learning takes place implicitly as the world model is updated with new information as the robot traverses the environment.

Included below are some examples of different high-level representations. Many of the papers referenced are distinguished by a discussion of the multisensor integration and fusion issues relevant to their proposed representation. Other representations are discussed as part of the descriptions of different mobile robots found in Sec. V.

A) Spherical Octree

Chen [9], [10] has proposed a "spherical octree" representation for use in mobile robot navigation. A spherical octree is an 8-ary tree structure that at its first level separates a spherical perspective view of the environment into eight octants corresponding to the children of the root node (the entire spherical environment perceived by the robot). Objects in the environment can be represented in the octree by recursively subdividing octants containing part of the object into eight more octants at the next lowest level, repeating this process to represent the object at increasingly finer resolution. The use of a spherical perspective view eliminates some of the limitations of the typical orthographic and planar perspectives used in optical sensing. It is also appropriate for sensors providing range information because range values can be represented as the radial distances from the sensor to the object. Information from each different sensor is used to reconstruct three-dimensional surfaces using a knowledge base of typical patterns for the sensor. The reconstructed surfaces are then fused together as part of the process of being represented in the octree structure.

B) Occupancy Grids and Neural Nets

Elfes [11]-[13] originally developed a cellular world model representation called the "occupancy grid" for use with a sonar equipped mobile robot. This representation has been extended in [14], [15] to allow for the integration of information from many different types of sensors. Bayesian estimation is used to fuse together each sensor's probabilistic estimate as to whether a cell in the grid is occupied by an object. The resulting grid can then be used to determine paths through unoccupied areas of the grid.

Jorgensen [16] has proposed dividing the environment into equal sized volumetric cells and associating each with a neuron. In a manner similar to the occupancy grid, the magnitude of each neuron's activation corresponds to the probability that the cell it represents is occupied. The neurons are trained using sensory information from different perspectives. "Associative recall" can then be used to recognize objects in the environment and "simulated annealing" can be used to find optimal global paths for navigation.

C) Graphs

Graph structures have been used to represent the local and topological features of the environment in order not to have to define a global metric relation between non-adjacent nodes (or points) in the graph. When landmarks or beacons are not used to correct cumulative position error, a global metric would contain too much uncertainty to be useful. Graph structures allow the topological features to be represented and reasoned with in an efficient manner. Kak, Roberts, Andress, and Cromwell [17], [18] used an attributed graph and Shafer-Dempster evidential reasoning to integrate sensory information for hierarchical spatial reasoning. Brooks [19] proposed the use of a graph to represent regions of potential collision-free motion termed "freeways" and "meadows." Each point in the graph corresponds to the location of a robot in configuration space at which sensory information was acquired, and is represented as an "uncertainty manifold." Each arc is labeled with a local measurement of the distance travelled between endpoints. The cumulative uncertainty of the robot as it moves from point to point in the graph is taken into account through the cascading of successive uncertainty manifolds.

D) *Labeled Regions*

Sensory information can be used to segment the environment into regions with properties that are useful for spatial reasoning. The known characteristics of different types of sensory information can be used to label some useful property of each region so that symbolic reasoning can be performed at higher levels in the control structure. Asada [20] proposed a method for building world models that uses the range images from sensors to create height maps of the local environment. Grey-levels represent the height of points in the map with respect to an assumed ground plane. The map is then segmented into regions and labeled. Sequences of maps, created as a robot moves, are integrated into a global map by overlaying pairs of height maps and then replacing the labels of corresponding regions in the height maps with a label determined according to a precedence procedure (e.g., if a region is labeled as unexplored in one height map and as an obstacle in another, the global map might label the region as an obstacle). The global map is then used for obstacle detection and path planning. Miller [21] developed a spatial representation that divided a map of an indoor environment into labeled regions. Each label is one of four possible types—each type referring to the number of degrees of freedom in the region (i.e., the two planar dimensions and the robot's orientation) that information from a sensor could be used to eliminate (e.g., the empty space in the center of the room is of type zero, a region near a corner is of type three, etc.). "Voronoi diagrams" are then used to group the regions into areas that correspond to a specific edge (or wall) in the environment.

E) *Production Rules*

The use of production rules in a control structure allows for a wide range of well-known artificial intelligence methods to be used for path planning and learning purposes. Lawton, Levitt, McConnell, and Glicksman [22] have used production rules to create schemas to represent both objects in terrain models and certain generic object types. Network hierarchies are created from the schemas that allow inference and matching procedures to take place at multiple levels of abstraction, with each level using an appropriate combination of the available sensors. Isik and Meystel [23] have used fuzzy-valued linguistic variables to represent the attributes of objects as part of a fuzzy logic-based production system for mobile robot control.

IV. Sensor Combinations

Due to the advantages and limitations of each type of sensor, most multisensor-based mobile robots use some combination of different sensor types to enable them to operate in environments ranging from roadways [24], [25] to unstructured indoor environments [26] to unknown natural terrain [5], [27], and to be used for applications including assembly [28] and nuclear power station maintenance [29]. Some sensors can not be used in a particular environment due to their inherent limitations (e.g., acoustic sensors in space), while others are limited due to either technical or economic factors. Obstacle detection with contact sensors necessarily limits the speed of a robot because contact must be made before detection can take place [30]. Laser sensors require an intense energy source, and they have a short range and slow scan rate—their use can also cause eye problems [31]. Vision sensors are critically dependent on ambient lighting conditions, and their scene analysis and registration procedures can be complex and time consuming [30]. Shaky, one of the first autonomous vehicles, used vision together with tactile sensors for obstacle detection [32]. JASON combined acoustic and infrared proximity sensors for obstacle detection, and also used these sensors for path planning [33]. The Stanford University Cart used acoustic and infrared sensors together with stereo vision for navigating over a flat terrain while avoiding obstacles [34]. Bixler and Miller [35] used simple low-resolution vision in their autonomous mobile robot to locate the direction of an obstacle, and then used an ultrasonic range finder to determine its depth and shape. Other combinations of sensors used in mobile robot systems have included: contact, infrared, and stereo vision [36]; contact and acoustic [37]; acoustic and stereo vision [38]; and stereo vision and laser range finding [39].

V. Selected Multisensor-Based Mobile Robots

Short descriptions of a selection of different mobile robots are provided below to illustrate the role of multisensor integration and fusion in their operation.

A) *HILARE*

The mobile robot HILARE combines contact, acoustic, two-dimensional vision, and laser range finding sensors so that it can operate in unknown environments [26], [40]-[42]. HILARE was the first mobile robot to create a world model of an unknown environment using information from multiple sensors [4]. Acoustic and vision sensors are used to create a graph partitioned into a hierarchy of locations. Vision and laser range finding sensors are then used to develop an approximate three-dimensional representation of different regions in the environment—constraints being used to eliminate extraneous features of the representation. The laser range finder is then used to obtain more accurate range information for each region. In order to provide a robust and accurate estimation of the robot's position, three independent methods are used: absolute position referencing by use of a beacon, trajectory integration without external reference, and relative position referencing with respect to landmarks in the environment [43]. Each of these methods is used in a complementary fashion to correct or reduce errors and uncertainties in the other methods. The information from a variety of sensors is integrated to provide the position of known objects and places relative to the robot. The shape of each object is represented as a polygon. Depending on the features of an object and its distance from the robot, an appropriate group of redundant sensors is selected to measure the object. The uncertainty of each sensor is modeled as a Gaussian distribution. If the standard deviations of all the sensor's measurements have the same magnitude, a weighted average of their values is used as the fused estimate of a vertex of the object; otherwise, the measurement from the sensor with the smallest standard deviation is used. The estimated vertices of the object can then be matched to known regions of the world model by finding an object in the model that minimizes the weighted sum of the distance between corresponding vertices.

B) *Navigation in a Known Domain*

Crowley [44]-[46] describes a mobile robot with a rotating ultrasonic range sensor and a touch sensor that is capable of autonomous navigation in a known domain. Information from a pre-learned global world model is integrated with information from both sensors to dynamically maintain a composite model of the local environment. Obstacles and surfaces are represented as connected sequences of line segments in two dimensions. Confidence as to the actual existence of each line segment is represented by an integer ranging from 1 (transient) to 5 (stable and connected). The uncertainty as to the position, orientation, and length of each segment is accounted for by allowing tolerances in the value of these attributes. Information from the global model and the sensors is matched to the composite local model by determining which line segment in the local model has the best correspondence with a given line segment from either the global model or sensors. The best correspondence if found by performing a sequence of tests of increasing computational cost based on the position, orientation, and length of the line segments relative to each other. The results of the matching process are then used to update the composite local model by either adding newly perceived line segments to the model or adjusting the confidence value of the existing segments. The local model can then be used for obstacle detection, local path planning, path execution, and learning.

C) Ground Surveillance Robot

The Ground Surveillance Robot described by Harmon [5], [47] is an autonomous vehicle designed to transit from one known location to another over unknown natural terrain. Vision and acoustic ranging sensors are used for obstacle detection. A laser range finder, together with a high-resolution gray-level camera and a low-resolution color camera, are used for distant terrain and landmark recognition. The information from the obstacle detection sensors is fused into a single estimate of the position of nearby obstacles by superpositioning distributions that represent each sensor's a priori probability of detection. A distributed blackboard is used both to control the various subsystems of the vehicle, and as a mechanism through which to integrate and fuse various types of sensor data. As part of the blackboard, a world model is used to organize the data into a class tree with inheritance properties. Each element in the world model has a list of properties to which values are assigned, some values being determined by sensory data. Terrain data are represented as triangular segments with the properties of absolute position, orientation, adjacency, and type of ground cover. In order to allow for a variety of fusion methods to be used, each element in the world model includes a time stamp and measures of its accuracy and confidence. When two or more sensor values are functionally dependent, changes in one value will propagate throughout the blackboard so that its dependent values reflect the change. When sensor values refer to the same property of an element, either a decision is made as to which of the competing values is to be used (e.g., the most recent value of the most accurate sensor), or the values are fused.

D) Stanford Mobile Robot

The Stanford Mobile Robot [48] uses tactile, stereo vision, and ultrasonic sensors for navigation in unstructured man-made environments. A hierarchial representation is used in its two-dimensional world model, with features close to the actual sensor measurements at the lowest level and more abstract or symbolic features at the higher levels. The uncertainty as to the location of the robot and the features in the environment is modeled with a Gaussian distribution. A Kalman filter is used to fuse the measurements from a sensor as the robot moves. An example of the application of this method is shown in Fig. 2. Fig. 2 (a) shows two points **a** and **b** as measured by the stereo vision sensor—first at location $\mathbf{p}_1$ and then at location $\mathbf{p}_2$. The uncertainty ellipses around the point measurements are elongated towards the sensor because the uncertainty due to distance is much greater than the angular uncertainty when calculated through stereo vision. The uncertainty due to distance is also greater for points further from their location of measurement (i.e., **b** is more uncertain than **a**). The two measurements of each point (e.g., $\mathbf{a}_1$ and $\mathbf{a}_2$) are not coincident because of the inherent error in the internal odometer sensor of the robot. In Fig. 2 (b), the uncertainty of the points and location $\mathbf{p}_2$ are shown with respect to $\mathbf{p}_1$. The uncertainty ellipse around $\mathbf{p}_2$ is elongated perpendicular to the direction of motion because the angular error of the odometer sensor is greater than its error in distance. The uncertainty, with respect to $\mathbf{p}_1$, of measurements $\mathbf{a}_2$ and $\mathbf{b}_2$ has increased because their uncertainty with respect to $\mathbf{p}_2$ has been compounded with $\mathbf{p}_2$'s locational uncertainty. In Fig. 2 (c), the Kalman filter is used to determine new fused estimates for both points (**a*** and **b***) that have reduced uncertainty with respect to both locations $\mathbf{p}_1$ and $\mathbf{p}_2$. The uncertainty of $\mathbf{p}_2$ with respect to $\mathbf{p}_1$ has also been reduced.

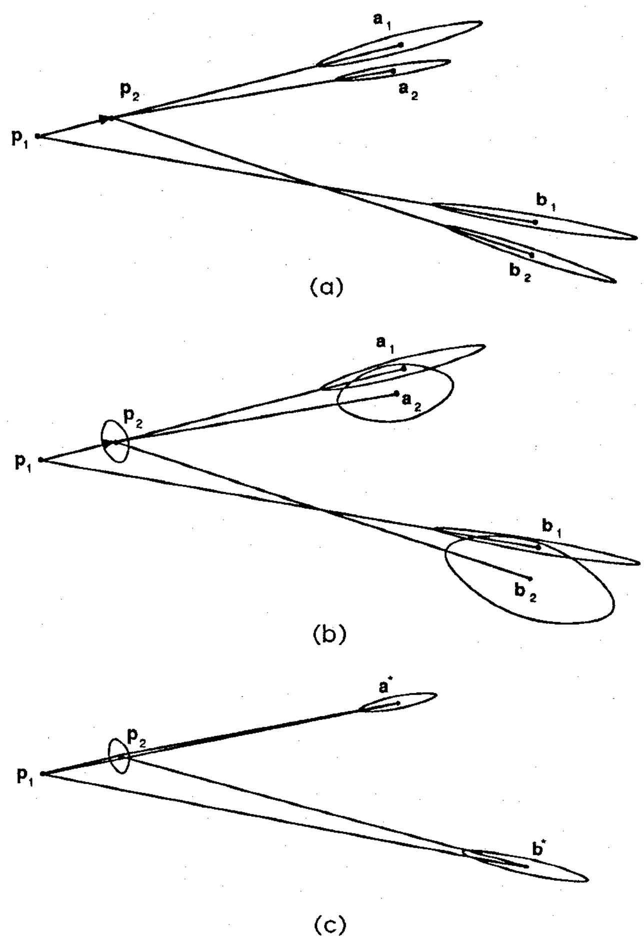

Fig. 2. Reduction in uncertainty as to the location of a robot (**p**) and two points (**a** and **b**) in the environment through the use of the Kalman filter to fuse measurements as the robot moves from $\mathbf{p}_1$ to $\mathbf{p}_2$. (a) Uncertainty before fusion of points **a** and **b** as measured from $\mathbf{p}_1$ and $\mathbf{p}_2$. (b) Uncertainty of **a**, **b**, and $\mathbf{p}_2$ with respect to $\mathbf{p}_1$. (c) Fused estimates for **a**, **b**, and $\mathbf{p}_2$ with respect to $\mathbf{p}_1$. (Adapted from Fig. 10 in Ref. [48].)

E) CMU's Autonomous Land Vehicles

The NAVLAB and Terregator are two vehicles developed at Carnegie-Mellon University's Robotics Institute as part of their research on autonomous land vehicles [24], [49]. Each vehicle is equipped with a color TV camera, laser range finder, and sonar sensors. The sonar sensors are used to detect nearby obstacles. The design of an architecture able to support parallel processing, and multisensor integration and fusion have been major goals of the research. The current system consists of several independently running modules that are tied together in what is termed a "whiteboard" control structure, which differs from a blackboard in that each module continues to run while synchronization and data retrieval requests are made. Data in a local world model is represented as tokens with attribute-value pairs. Tokens representing physical objects and geometric locations consist of a two-dimensional polygonal shape, a reference coordinate frame that can be used to transform the location to other frames, and time stamps that record when the token was created and the time at which sensor data was received that led to its creation. When range data, measured by the camera and laser range finder at different times and locations on the vehicle, are to be fused, the coordinate frames of the tokens created by each sensor for this data are first transformed to a common vehicle frame and then transformed forward to the same point in time. The data is now fused, resulting in the creation of a new token representing the fused data.

F) The DARPA Autonomous Land Vehicle

The Autonomous Land Vehicle (ALV) [25], [27], [50]-[52] built by Martin Marietta is part of the Defense Advanced Research Projects Agency's (DARPA) Strategic Computing Program. The ALV is intended to be a testbed designed for demonstrating the state of the art in autonomous vehicle research [52]. A number of companies and universities are currently working on different research aspects of the project. In the initial stages of the project, the ALV was used in road-following applications [25], [50], [53]; in more recent stages, obstacle avoidance [52] and autonomous cross-country navigation [52], [54] capabilities have been demonstrated. Future research is aimed at enhancing the operational speed and robustness of the ALV, and adding capabilities like landmark recognition [52].

In road-following applications [25], [52], the ALV uses sonar to determine its height, tilt, and roll with respect to road surfaces directly beneath it. Complementary information from a laser range scanner and two color video cameras is used for obstacle detection. The color video information is used to locate roads because the laser range information can easily be confused if there is very little difference in depth between the road and surrounding areas. Laser range information is used to obtain accurate descriptions of the geometrical features of obstacles on the road because, unlike the video information, it is not sensitive to poor lighting conditions and shadows. After being transformed to a common world coordinate system, the video information is used both to determine the boundaries of the road for path planning and, after being integrated with similarly transformed laser range information, for obstacle recognition.

In autonomous cross-country navigation applications [27], a hierarchial control system is used to provide the ALV with the flexibility needed for operation over natural terrain. At the lowest level in the hierarchy, "virtual sensors" and "reflexive behaviors" are used as real-time operating primitives for the rest of the control system [54]. Virtual sensors combine information from physical sensors with appropriate processing algorithms to provide specific information to associated reflexive behaviors. Combinations of behaviors and virtual sensors are used to handle specific subproblems that are part of the overall navigation task. In this application, a laser range scanner, together with orientation sensors to determine the pitch, roll, and x and y position of the vehicle, were used to provide information needed to create overhead map view representations of the terrain called Cartesian Elevation Maps (CEM). Other range sensors, such as stereo vision, could also be used to create CEM's. Smoothing procedures are applied to the CEM's to fill in detail not provided by the sparse laser range information. As the ALV travels over the terrain, CEM's are fused together to provide a means for selecting traversable trajectories for the vehicle.

V. Conclusion

In the future, mobile robot development and multisensor integration and fusion research will continue their symbiotic relationship: both theoretical and practical techniques of multisensor integration and fusion will increase the ability of mobile robots to operate autonomously in unknown and dynamic environments, and mobile robots will, in turn, continue to provide data-rich platforms on which to test new integration and fusion techniques. As current progress in VLSI technology continues, the development of integrated solid-state chips containing multiple sensors will enable mobile robots to use an increasing number of sensors at lower cost without increasing their power requirements. It is likely that so-called "smart sensors" [55] will be developed that will allow many low-level signal and fusion processing algorithms to be included in circuits on the chip. A smart sensor might also provide a better signal-to-noise ratio, and abilities for self-testing and calibration.

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