ENVIRONMENT IDENTIFICATION FOR AUTONOMOUS MOBILE ROBOT OPERATION

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ABSTRACT *A model based image analysis system is presented for autonomous mobile robot operation in unstructured environments. The system exploits a hierarchical representation of environments as the basis of image processing and system integration. Before maneuvering mobile robots, the system accepts the operator's message to generate an instance of a task goal dependent sub-description of physical environments, called a work space model. During mobile robot operation, the system autonomously identifies the work space model for in-process verification of the maneuver plan and for on-line vehicle mechanism control. The methodology is verified through experimental studies using a prototype system.*

INTRODUCTION

The introduction of mobile robots is urgently required for ill-defined tasks, including maintenance and inspection, in unstructured environments [6] [8]. Because of the uncertainty of task goal, the target object must be specified at each maneuver by a human operator. In unstructured environments, due to incomplete comprehension of environments, the path to the target object must be decided at each step through observation of surroundings. Thus, a tight human-robot linkage is urgently required for mobile robot application to ill-defined tasks in unstructured environments. However, since robots are large compared to the available operation space and their mechanism is quite different from that of human body, simple remote control is not easy. In addition, since general environments are too complicated to describe using a priori building data and mobile robot motion is susceptible to road conditions, it is impractical to generate a comprehensive mechanism control plan before robot operation. Thus, autonomous operation and hence environment recognition is crucial in practical situations.

In conventional robot applications, including assemblage and carriage, environment recognition before robot operation is sufficient for automatic generation of an operating plan, because the task goal can be decided based only on recognition of the object's location. However, in ill-defined tasks, it is not easy for a human operator to decide the goal of robot operation because comprehension of the situation, necessary to make a decision, itself requires detailed, and very often active, observation of the scene. This implies that maneuvering during task execution should be re-planned at each task step, based on recognition of the environment, which may be altered by the robot's operation. Thus, a mobile robot should be maneuvered through interactive operation by a human operator [4].

Noting that *local planning* in a *local environment* is crucial to interactive operation, the robot system must be designed within the framework of an *open world paradigm* [5]: a task goal dependent sub-description of a physical environment, called the work space model, is generated as a basis for task planning and vehicle mechanism control. According to the open world paradigm, autonomous robot operation is formulated by identification of the work space model through various level s of observation. Dependence of the work space model on the task goal implies that the work space model itself should be re-generated at each robot operation. The work space model is generated as a specification of abstract description of a scene, which is dependent on the kind of the task to be executed by observation of the scene. Robot operation in an unstructured environment requires consistency analysis between generated work space model and observed scene for updating the operation plan at each maneuver.

The consistency analysis is formulated by identification of image features extracted from the observed scene. Due to continuous variation of the scene caused by continuous view point shift during maneuvering, an efficient model matching procedure must be introduced for self location estimation for tracking the planned route. Location estimation is formulated by identification of view point parameter for transforming the work space model to imagery equivalent to the observed scene. In this paper, an image analysis system is presented for interactive model generation, object contour detection and self location estimation in environment identification for autonomous mobile robot operation.

MODEL BASED APPROACH

Various kinds of knowledges are required for autonomous mobile robot operation, as illustrated in Fig. 1: Geometric data is necessary for estimating the relative location of the vehicle mechanism. Literal description of the object's status and mutual relation between objects are useful for consistency analysis of the motion plan. Representation of maneuver concept is crucial in planning the route to the destination. This knowledge should be integrated in the work space model for autonomous mobile robot operation: For example, measurements of vehicle mechanism rotation must be interpreted, by maneuver model, into the current location relative to landmark objects for generating a sequence of sub-goals, based on the relative locations of landmark objects and for deciding steering and speed to the next sub-goal. At the same time, this knowledge should also be mutually associated for interactive robot operation: For example, in specifying a landmark object for a current task goal, the image of the landmark object must be detected in the observed scene. Thus, the environment for robot operation must be described in terms of a roadway map where the location and various attributes of landmark objects are stored.

To generate the work space model as the basis for interactive operation of autonomous mobile robots, a hierarchical representation of the space concept [2] is introduced for extended classes of buildings as illustrated in Fig.2. In this representation, a spatial point is specified in terms of the quadruple of (building floor zone node). In this quadruple, building, floor and zone are essentially symbolic representations in each scope of a specific spatial point and the node, a specific spatial point at which maneuver plan can be altered, is essentially the coordinate of a spatial point with respect to the coordinate system attached to the zone. At each node, all visible landmark objects are stored. In other words, each landmark object is associated to every node from which the landmark object can be observed.

The other hierarchy, consisting of route and path, is introduced to describe the concept of maneuver in the space hierarchy. This implies that the roadway in the building is represented in terms of (route path) - pair. The route and path are chains of zone symbols and node symbols, respectively. At each path, a motion primitive symbol is associated to adapt the vehicle mechanism to the condition of the roadway, including flat floor, staircase, etc. In other words, the path is the segment of the roadway divided in terms of uniformity of roadway condition. Available route symbols are associated to each zone symbol,. Each zone has specific node located at its entrance or exit, called a junction. By associating route symbol to junction symbol, symbolic level maneuver and geometric level maneuver are unified in the environment description without any direct route - path association mechanism.

The space hierarchy and maneuver hierarchy are combined to plan and operate of a mobile robot in the building. To efficiently extract landmark objects during maneuvering, a set of body_maps is first generated and attached to each node. The body_map is a local aggregation of landmark objects with respect to possible orientation at each node: i.e., in each body_map, only landmark objects are distributed in front of the robot, which is located at the node in a specific orientation. The work space model is generated as an instance of the body_map with current robot location, during each maneuver. Noting that mutual association between (building floor zone node) representation of spatial points and (route path) representation of roadways, maneuver plan is generated by solving a search problem in the node graph and the environment is recognized through matching of the observed scene with the sequence of landmark object sets provided in accordance with the maneuver.

IDENTIFICATION OF WORK SPACE MODEL

Noting that the work space model is a partial description of the environment described in Fig. 2, the identification procedure is divided into two steps: the generation of the model description before robot operation and model matching with observed imagery through maneuvering.

According to the environment description in terms of the combination of (building floor zone node) - hierarchy and (route path) - hierarchy, the work space model is generated following the template illustrated in Fig. 3: To specify the a priori description of the work space model, the symbols of landmark objects are copied from the body_map associated with the current node. The current goal is specified by the planner which generates a chain of nodes based on the (route path) - description of roadway and destination node specified by the human operator. The motion primitive symbol is specified using the roadway condition associated with the path symbol. The initial value of the current location and direction data, which is updated by the vehicle mechanism controller during the maneuver, is computed based on the locations of current node and following nodes.

The a posteriori work space model is generated by matching the a priori model through measurements. Before robot operation, the location of a specific landmark object, decided by the human operator, is recognized through analysis of observed imagery. In recognizing the object location, knowledge of the specified landmark object is extracted from a_kind_of hierarchy of object and linked with the (building floor zone node) - hierarchy for representation of generation scenario of a posteriori work space model. Fig. 4 illustrates an example of a scenario in which the generation procedure of the work space model and image analysis method for matching the object to be filled in the work space model are stored in the space hierarchy and the object hierarchy, respectively.

The generated a posteriori work space model is identified through matching with observations and updating the model description during maneuvering. In the identification of the work space model, predictions for observations are generated and matched with measured data to evaluate the disparity of the model and observed data. The current location and direction data in the work space model are updated by the vehicle mechanism controller. By combining location and direction data and geometric data of landmark objects extracted from the body_map, the scene to be observed is predicted for in-process decision making on path selection and for on-line self location estimation. The result of decision making is recorded in the work space model and the results of self location estimation is fed back to the vehicle mechanism controller for tracking to a planned route under disturbances during maneuver.

RECURSIVE IMAGE ANALYSIS FOR MODEL MATCHING

The multi modal description of the work space model is matched with observed imagery through two categories of procedures: structural - syntactic analysis for matching literal description and geometric - statistical analysis for evaluating geometric disparity. To exploit the matching results for in-process decision making and on-line self location estimation, the matching procedures should be formulated in terms of recursive algorithms. In addition, to utilize the matching results for interactive robot operation within the open world paradigm, matching procedures should be integrated into an inclusion based image analysis system.

To combine the two categories of image analysis methods, the contour imagery of landmark objects is described in terms of linear segments as illustrated in Fig. 5.

The probability of segment distribution in the image plane is assumed to be as follows [2]:

$$(1a)\quad \Pr\{z\in \mathbf{O}\} = exp[-(\phi'[i]z-\rho[i])^2/2\gamma[i]^2] / \sqrt{2\pi}\gamma[i], \qquad \gamma[i]>0,$$

$$(1b)\quad z = [\, x, y\,]'\in\Sigma_i,$$

$$(1c)\quad \phi[i] = [cos\theta[i], sin\theta[i]]'.$$

Let the contour distribution be observed through recursive edge detector described by:

$$(2a)\quad y(z) = h[\Xi[i]](z) + v(z), \;\; z\in\Sigma_i,$$

$$(2b)\quad h[\Xi[i]](z) = \begin{cases} 1: & for\,|\Delta f| \geqq \mu, \\ 0: & for\,|\Delta f| < \mu, \end{cases}$$

where,

f	:	gray level distribution of observed imagery
Δ	:	2D Laplacian operator
v	:	noise pattern,
y	:	observed image data,
μ	:	threshold.

The uniformly distributed random dots in the edge pattern is reduced by tempo - spatio aggregation implemented as:

$$(3)\quad \partial\psi[i]/dt = \Delta\psi[i] + k_i[y-\psi[i]], \;\; k_i>0, \quad i=1,2,3,\ldots,$$

where,

$\psi[i]$: filtering results.

The filtering mechanism (3) is implemented by the simple recursive image processing algorithm illustrated in Fig. 6.

Let the a priori estimates of the segment parameter associated with the contour imagery be restricted in the discrete Hough parameter space, as illustrated in Fig. 7.

Then, by combining the least squares and the maximum likelihood methods, the segment parameter estimate is computed as the following algorithm:

Step-4a: *Assign an initial value for estimate* $\hat{\xi}[i,j]\equiv[\hat{\phi}[i,j],\hat{\rho}[i,j]]'$ *and compute* $\hat{\phi}[i,j]=[cos(\hat{\theta}[i,j]), sin(\hat{\theta}[i,j])]'$.

Step-4b: *Specify* (i^*,j^*) *for each* $\zeta\in\psi$ *satisfying the inequality:*

$$|\,\hat{\phi}[i^*,j^*]'\zeta-\hat{\rho}[i^*,j^*]\,| < \epsilon/2,$$

where,

$$\Psi\equiv\{\zeta\in\Sigma \mid \psi(\zeta) \geqq \mu\}.$$

Step-.4c: *Apply the least square method to estimate parameters* $a[i^*,j^*]$ *and* $b[i^*j^*]$ *thus minimizing the error*

$$\sum|\,\zeta_2-a[i^*,j^*]\zeta_1-b[i^*,j^*]\,|^2,$$

or

$$\sum|\,\zeta_1-a[i^*,j^*]\zeta_2-b[i^*,j^*]\,|^2,$$

for $\zeta=[\zeta_1,\zeta_2]'\in\Psi$.

Step-4d: *Compute* $\ddagger\xi[i^*,j^*]\equiv[\tilde{\phi}[i^*,j^*],\tilde{\rho}[i^*,j^*]]'$ *based on* $a[i^*,j^*]$ *and* $b[i^*,j^*]$.

Step-4e: *Update* $\hat{\xi}[i,j]$ *by* $\tilde{\xi}[i^*,j^*]$ *and compute* fl$\phi[i,j]$ *as*

$$\hat{\phi}[i,j] = [cos(\hat{\theta}[i,j]), sin(\hat{\theta}[i,j])]'.$$

Then, return to **Step-4a.**

The simulation results of segments detection are illustrated in Fig. 8, 9 and 10, where the set of parameters associated with two linear segments are demonstrated to be detected simultaneously with sufficient accuracy.

In the interactive generation and consistency analysis of work space model, a list based matching scheme [7] is invoked to analyze a syntax of the contour distribution associated with the landmark object in noisy edge pattern corrupted by semantic noise including background object contours. In the list matching procedure, the linear segment distribution is described in terms of the following list of Hough parameters associated with contours imagery:

$$(5)\quad \Xi[i] = [\xi[i;1],\xi[i;2],\xi[i;3],\ldots,\xi[i;m]], \;\; i=1,2,3,\ldots.$$

where Hough parameters are arranged by the ordering rule:

$$(6a)\quad \theta_i < \theta_j \Rightarrow \xi_i < \xi_j,$$

$$(6b)\quad \theta_i = \theta_j \text{ and } \rho_i < \rho_j \Rightarrow \xi_i < \xi_j.$$

The list matching procedure is defined as the inclusion based matching rule:

$$(7)\quad \Xi^r{}_{i^*} \subset \Xi^d \Rightarrow \Xi^r{}_{i^*} \text{ matches } \Xi^d.$$

where Ξ^d denotes the list of detected parameters:

$$(9)\quad \Xi^d = [\xi^d{}_1, \xi^d{}_2, \xi^d{}_3,\ldots, \xi^d{}_m].$$

and Ξ^r denotes the list of reference parameter list defined as follows:

$$(10a)\quad \Xi^r = [\Xi^r{}_1, \Xi^r{}_2, \Xi^r{}_3,\ldots, \Xi^r{}_M],$$

$$(10b)\quad \Xi^r{}_i = [\xi^r{}_i(1), \xi^r{}_i(2), \xi^r{}_i(3),\ldots, \xi^r{}_i(n)], \quad i=1,2,\ldots,M,$$

The schematics of the list matching procedure is illustrated in Fig. 11 where the reference list $\Xi^r{}_1$ is shown to be matched with the detected list Ξ^d.

The observed edge pattern and reference pattern generated by perspective projection of the object contours stored in work space model are matched for estimating the current location of mobile robots within the framework of the pattern kinetics concept. The matching mechanism is described in terms of the following recursive algorithm [1]:

(11a) $d\Phi/dt = \Delta\Phi + \chi[f_r(\theta)]$,

(11b) $\psi(s) = \chi[f_m]\nabla\Phi(s)$,

(11c) $d\theta/dt = \pi[\psi]$,

(11d) $$\pi[\psi] = -\int_{\Sigma} \Omega(s)\psi(s)ds.$$

where,

f_m : observed pattern,
f_r : reference pattern,
θ : location estimate.

The stability of recursive algorithm (11) is ensured if the weighting function satisfies the following a mild condition, called structural consistency:

C-12: $\alpha(s)[\partial\varphi(s)/\partial\theta] = \Omega(s),\ 0<\kappa<\alpha(s)$,

where,

φ : optical flow between observed and reference patterns.

The recursive algorithm (11) can be implemented by simple hardware using a frame memory and a set of local pattern processors as illustrated in Fig. 12. The feedback processor can be implemented by the following locally parallel algorithm [3]:

(13.a) $\Phi(i,j) \leftarrow \beta\tilde{\Phi}(i,j) + (1-\beta)\Phi(i,j),\ 0<\beta<1$,

(13.b) $\tilde{\Phi}(i,j) = \Phi(i-1,j) + \Phi(i,j+1) + \Phi(i+1,j) + \Phi(i,j-1)$,

(13.c) $\Phi(x,y) = \Phi(\cdot,\cdot)\cdot exp[-\rho^2/4\tau]/4\pi\tau$,

ρ : distance to source,
τ : sampling time interval.

Algorithm (13) can be executed by a simple network consisting of look up tables (LUTs) and adder as shown in Fig. 13. The convergence efficiency of the recursive equation (12) is examined through simulation studies of a simple 2D pattern detection process as illustrated in Fig. 14 where the initial location of adjustable pattern and target pattern are described. In these simulations, the disparity between an adjustable pattern generated by the location estimate and the target pattern is evaluated by eq. (12) to update the location estimate. These simulation results demonstrate that the location estimate converges to the unknown location of target pattern much faster than the saturation of the potential field approximated by the recursive equation (12). The efficiency is a great advantage in on-line location error estimation.

EXPERIMENTS

A prototype of the environment identification system has been developed using mini- and micro- computer systems enhanced by array processors for real-time image data analysis. Hardware schematics are illustrated in Fig.15 where a graphics display is introduced for monitoring the status of the environment model and the results of image analysis.

Experimental results using the prototype system are illustrated in Fig.16 - 19. The results of work space model generation using an interactive mapping scheme are illustrated in Figs.16, where the object specified through a graphics display is shown to be successfully identified and stored in work space model. In this case, the distance error caused by the object specification through graphics interface was about ±5cm for an object located about 5m from the TV camera. Although the distance error may be too large to be used for direct robot planning, the contour structure was successfully analyzed to identify the object as the "main pipe".

The results of image consistency analysis within the framework of the list matching scheme are illustrated in Fig. 17 where the structure of contour imagery in a noisy edge pattern is demonstrated to be extracted successfully.

Fig. 18 illustrates experimental results of location error estimation via the pattern kinetics algorithm. The experimental evaluation of the estimation error in the pattern kinetics algorithm is shown in Fig. 18, where the pattern kinetics algorithm exhibits sufficient steady state accuracy.

As demonstrated in these figures, the methods proposed in this paper can generate and identify the work space model for extended classes of practical environments.

CONCLUDING REMARKS

A model based image analysis system was presented for environment identification. Two categories of image processing methods were developed for structural and geometric consistency analysis in instance generation, consistency analysis and disparity evaluation of hierarchical representation of environments. The proposed method was verified through a series of experiments using a prototype system.

From the view point of practical application, the development of an interface system to a large scale plant database is required. Additional research on deep information extraction and interactive robot programming is also expected for application of developed methodology to practical monitoring and maintenance tasks.

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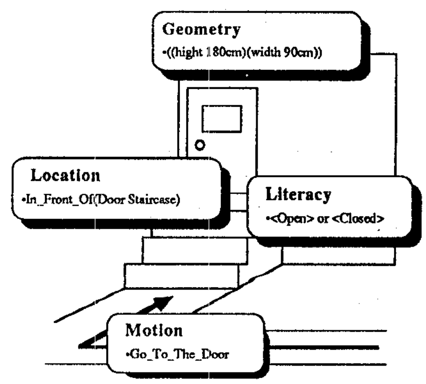


Fig.1 Knowledges Required for Autonomous Robot Operation

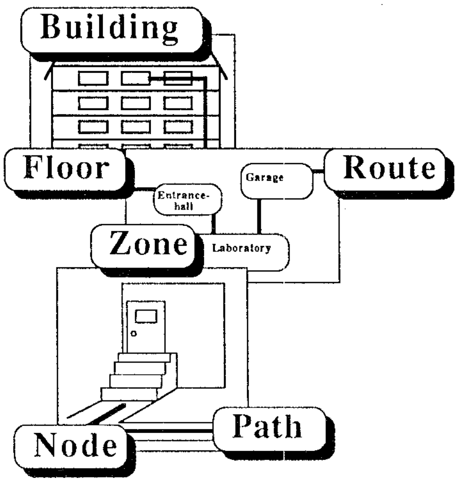


Fig.2 Hierarchical Representation of Buildings

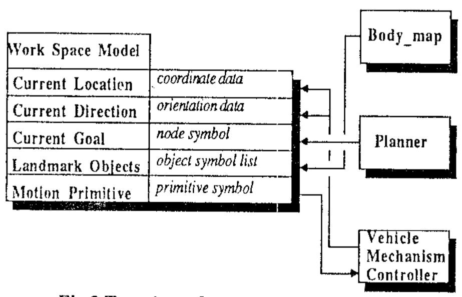


Fig.3 Template of Work Space Model

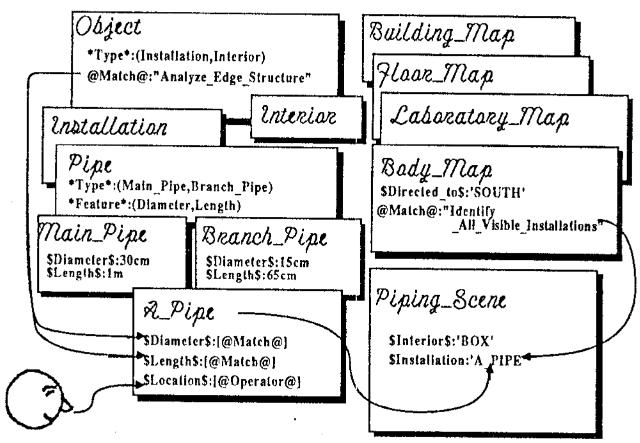


Fig.4 A Scenario for Work Space Model Generation

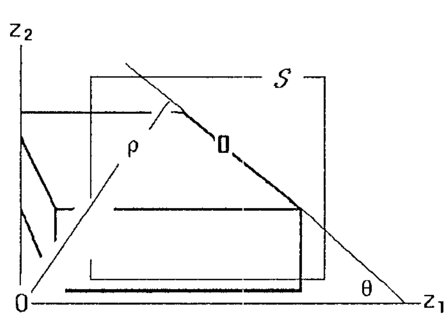


Fig.5 Mathematical Model of Object Contour Imagery

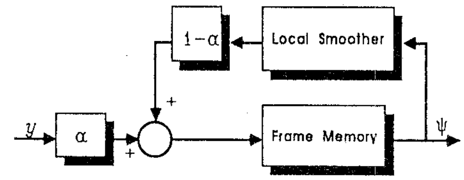


Fig.6 Recursive Image Processor for Noisy Dot Reduction

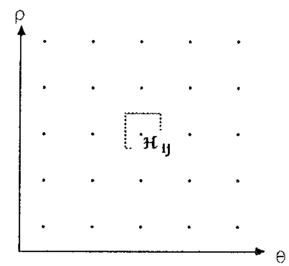


Fig. 7 Partition of Hough Parameter Space

x:

	0	1	2	3	4	5	6	7	8	9	A	B	C	D	E	F
y:0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
y:1	0	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0
y:2	0	0	0	1	1	0	0	0	0	0	1	0	0	0	0	0
y:3	0	0	0	0	0	1	1	0	0	0	1	0	0	0	0	0
y:4	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0
y:5	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0
y:6	0	0	0	0	0	0	0	0	1	0	1	1	0	0	0	0
y:7	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0
y:8	0	0	0	0	0	0	0	0	1	0	0	0	0	1	1	0
y:9	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1
y:A	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
y:B	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
y:C	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
y:D	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
y:E	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
y:F	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0

(a) Segments to Be Detected

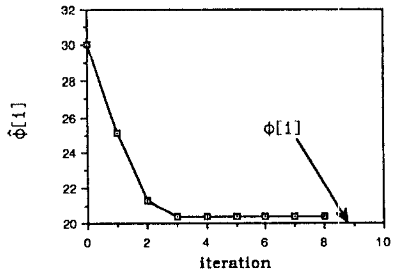
ρ

θ

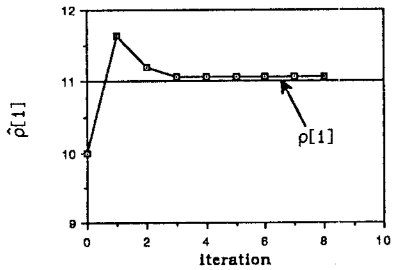
	i_abs							
	1	2	3	4	5	6	7	8
i_arg:1	.	.	.	.	.	.	.	.
i_arg:2	.	.	.	.	.	*	.	.
i_arg:3	.	.	.	.	.	.	.	.
i_arg:4	.	.	.	.	.	.	.	.
i_arg:5	*	.	.	.	.	.	.	.
i_arg:6	.	.	.	.	.	.	.	.

(b) Detection Results

Fig. 8 Simulation Results of Segments Detection

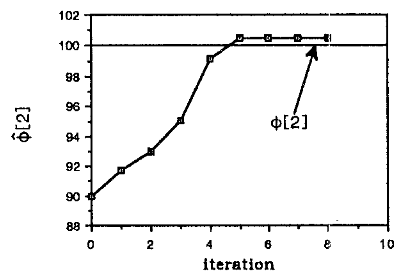


(a) Direction Parameter Estimation Results

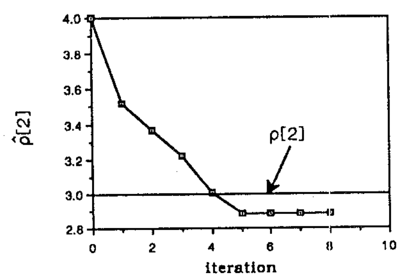


(b) Distance Parameter Estimation Results

Fig. 9 Simulation Results of Segment Detection-1-



(a) Direction Parameter Estimation Results



(b) Distance Parameter Estimation Results

Fig. 10 Simulation Results of Segment Detection-2-

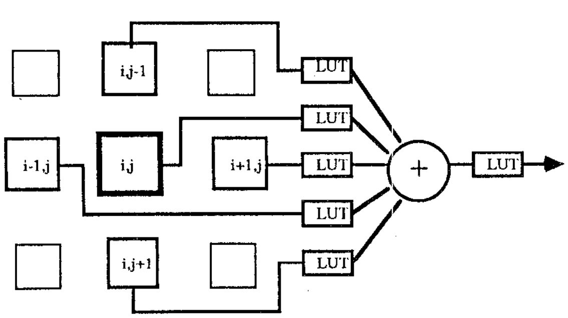


Fig.13 Hardware Implementation of Feedback Processor

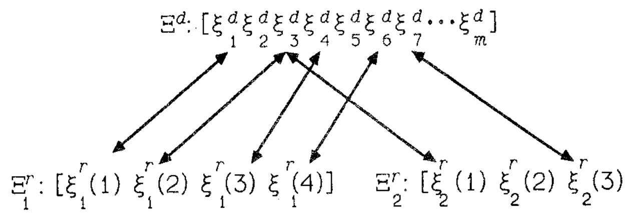


Fig.11 Schematics of List Matching Concept

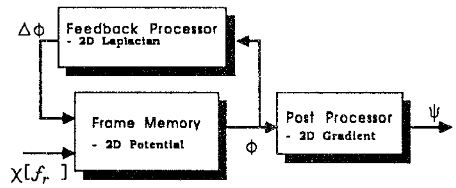
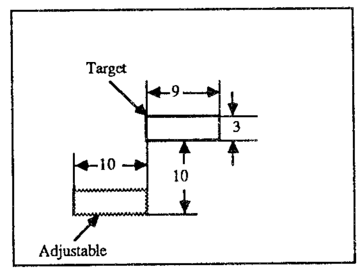
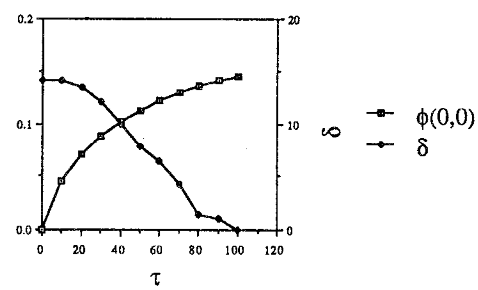


Fig.12 Hardware Implementation of Recursive Algorithm (11)



(a) Simulation Model



(b) Convergence of Location Error

Fig.14 Simulation Results of Recursive Algorithm (11)

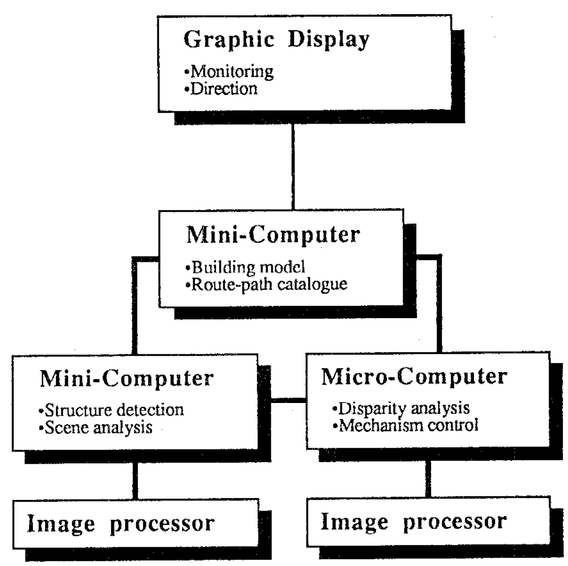
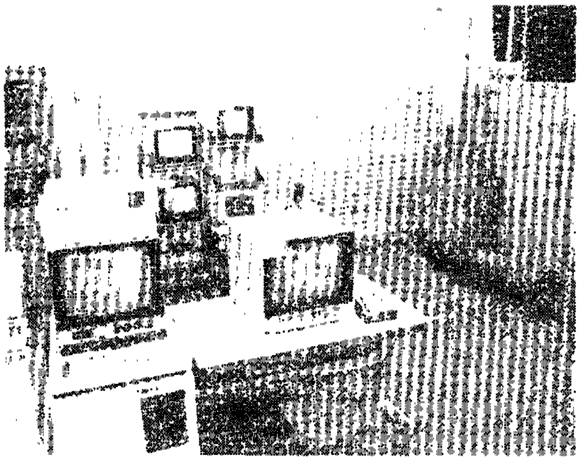
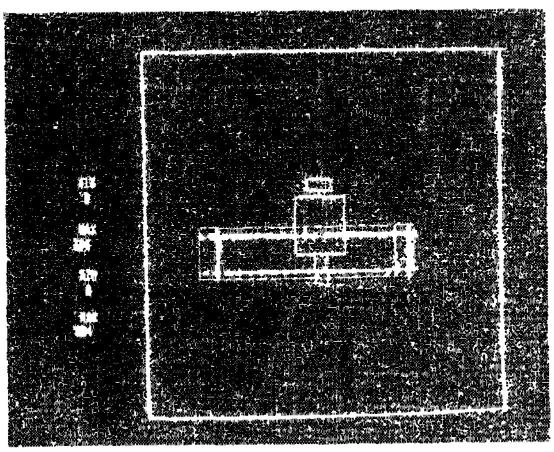


Fig.15 Schematics of Prototype System

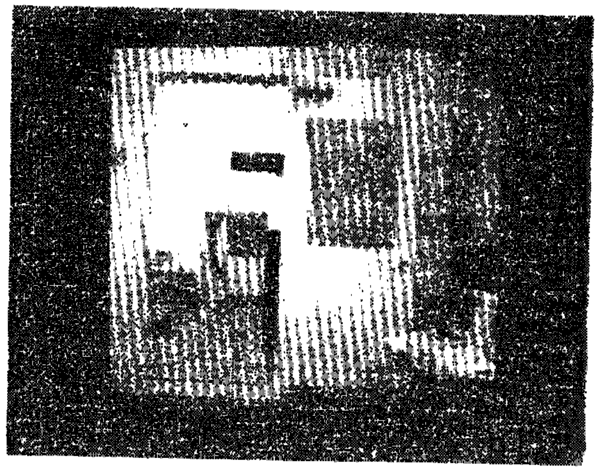


(a) Scene To Be Modelled

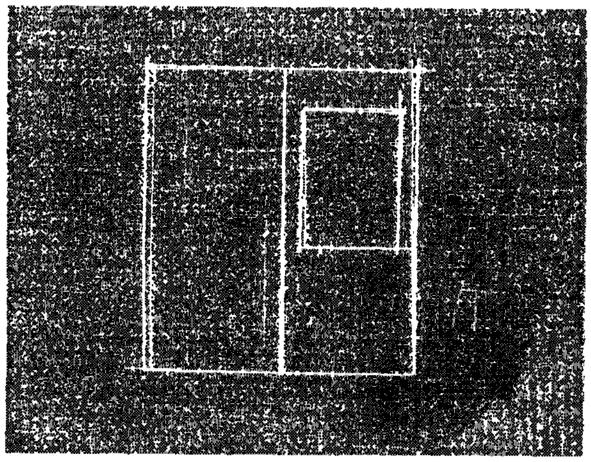
(b) Graphics Interface for Object Specification



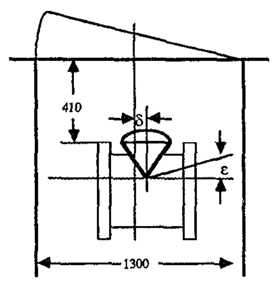
(c) Mapping Results
Fig. 16 Experimental Results of Interactive Mapping



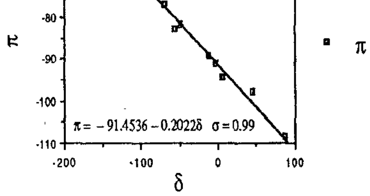
(a) Scene to be Analysed



(b) Extracted Structre of Contour Imagery
Fig. 17 Image Structure Analysis via List Matching



(a) Experimental Conditions



(b) Measured Location vs Estimated Location
Fig. 18 Relative Location Estimate via Model Matching