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AUTONOMOUS DETECTION OF OBJECTS FROM RANGE DATA MEASUREMENTS

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The overall objective of this study is to provide autonomous detection of obstacles or objects within a given field of view using noisy range data measurements as might be obtained from a laser rangefinder. Specifically, the goal is to provide simplified and efficient computer procedures suitable for filtering and processing the range data to detect objects. The particular procedure studied involves a single term state vector (range) with adaptive

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20. ABSTRACT (CONT'D)

procedures for handling objects on a sloped plane. The range data is processed by incrementally varying elevation angle for fixed azimuth angle. The edges of objects are detected using a Bayesian decision procedure on the filtered range data.

Results are presented showing the minimum object size that can be detected as a function of false alarm rate, Bayesian decision criteria, measurement noise level, and covariances of the artificial noise levels added to the filter to minimize false alarms. The artificial noise covariances can be either in the form of system (plant) noise or measurement noise. Results indicate that the most efficient approach to minimizing false alarms in terms of minimizing detectable object size is to adjust the Bayesian decision criteria. The least efficient approach is to artificially add system noise covariances.

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INTRODUCTION

The successful development of an autonomous 3-D vision system would be of considerable value and importance to future national defense related systems as well as numerous domestic applications. Within the U.S. Army, applications for such a vision sytem would include autonomous navigation of various Army vehicles and weapon systems, ammunitions supply, autoloading systems, and target recognition.

Numerous approaches are currently being investigated for 3-D systems. One such potentially successful approach involves analysis of range data as might be obtained from a laser rangefinder. One of the authors of this report, C. N. Shen, has been conducting studies since 1968 at Rensselaer Polytechnic Institute on application of an autonomous laser rangefinder vision system for a Mars rover vehicle (see Reference 1 for a summary of this work). It is assumed herein that a matrix of systematically measured ranges is obtained for a given field of view. This matrix can then be treated analytically for purposes of object location, navigation, and scene analysis.

Our current study deals with a small aspect of the overall problem. The specific problem considered is edge detection of objects on a sloped, possibly wavy plane. An example might be the location of boulders, rocks, craters, sharp hills, trees, etc. in the autonomous navigation of a vehicle over terrain. The procedure used for edge detection is called RES (rapid

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[1]Shen, C. N., "Autonomous Navigation for Mobile Robot Vehicles Over Hilly Terrain Using Rangefinder Measurements," Proc. Robot Intelligence and Productivity Conference, Wayne State University, Detroit, MI, November 18-19, 1983.

estimation scheme) by Sonalkar, Sanyal, Kim, and others (refs 2-4). RES is basically a decision-directed estimation approach in which the range matrix which contains both measurement and system noise is processed one column (or row) at a time. One column, for example, of the range matrix is a series of range measurements obtained at different incrementally varied elevation angles (β_i) for fixed azimuth angle (θ_j), as shown in Figure 1. This vector is analyzed by stepping through each range measurement element one at a time and using a combination of (1) Bayesian decision criteria to detect impulses (edges of objects), (2) impulse estimation if an edge is detected, and (3) Kalman filtering if no edge is detected. The system model used for the Kalman filter is a plane with fixed or adaptive slope.

The particular numerical procedure presented herein involves a single term state vector (range) with adaptive procedures for handling objects on a sloped plane. This results in a procedure nearly twice as fast as approaches using a two-term state vector (range and slope) as used by Kim et al (ref 4).

The main goals of the work presented in this report are to (1) study approaches for minimizing false alarms given a minimum size object to be detected, and (2) determine specifications for accuracy of instrumentation, such as a laser rangefinder, required to detect given object sizes.

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[2]Sonalkar, R. V. and Shen, C. N., "Mars Obstacle Detection by Rapid Estimation Scheme from Noisy Laser Rangefinder Readings," Proc. of the Milwaukee Symposium on Automatic Computation and Control, Wisconsin, April 1975, pp. 291-296.

[3]Sanyal, P., "Rapid Estimation of States by Detecting Unknown Impulse Inputs at Unknown Times," PhD Thesis, Rensselaer Polytechnic Institute, Troy, NY, University Microfilms, Ann Arbor, MI, 1973.

[4]Kim, C. S., Marynowski, R. C., and Shen, C. N., "Obstacle Detection Using Stabilized Rapid Estimation Scheme With Modified Decision Tree," Proc. of JACC, Philadelphia, PA, October 1978.

SINGLE TERM RAPID ESTIMATION SCHEME

In this and the next section a summary of the RES procedure is presented. For more detailed discussion of the Kalman filter, impulse estimation and Bayes' risk analysis, the reader is referred to References 3, 5, and 6.

Range measurements are assumed available in the form of a matrix Z in which the element z_{ij} represents the measured ranges for elevation angle β_i and azimuth angle θ_j, as shown in Figure 1. In the RES procedure only one column (row) of this matrix is processed at a time and edges of objects, if any, detected. In this report only column processing will be considered where it is assumed that θ_j is arbitrarily fixed. Each column is processed in a similar manner, and the outline of object edges inferred from the results of the column processing. Row processing can also be accomplished for more object detail.

For a given column, processing begins with the point at the highest elevation (lowest value of β in Figure 1). Each subsequent β point is then incrementally considered. At a given point a Bayesian decision criterion is used to determine if a jump in actual over expected range is indicated. If not, Kalman filtering is used to obtain a better state estimate at the next point, and so on. If an impulsive jump is detected, then the measured range at the next point becomes the starting point for continued processing. After

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[3]Sanyal, P., "Rapid Estimation of States by Detecting Unknown Impulse Inputs at Unknown Times," PhD Thesis, Rensselaer Polytechnic Institute, Troy, NY, University Microfilms, Ann Arbor, MI, 1973.
[5]Kalman, R. E., "A New Approach to Linear Filtering and Prediction Problems," Trans. of ASME, Journal of Basic Engineering, March 1980, pp. 35-45.
[6]Sage and Melsa, Estimation Theory With Applications to Communications and Control, McGraw-Hill, New York, 1971, Chapter 5, "Decision Theory."

an edge detection the Kalman filter is reset to ignore previous data. The entire column of ranges is processed in this manner storing location and values of recorded jumps.

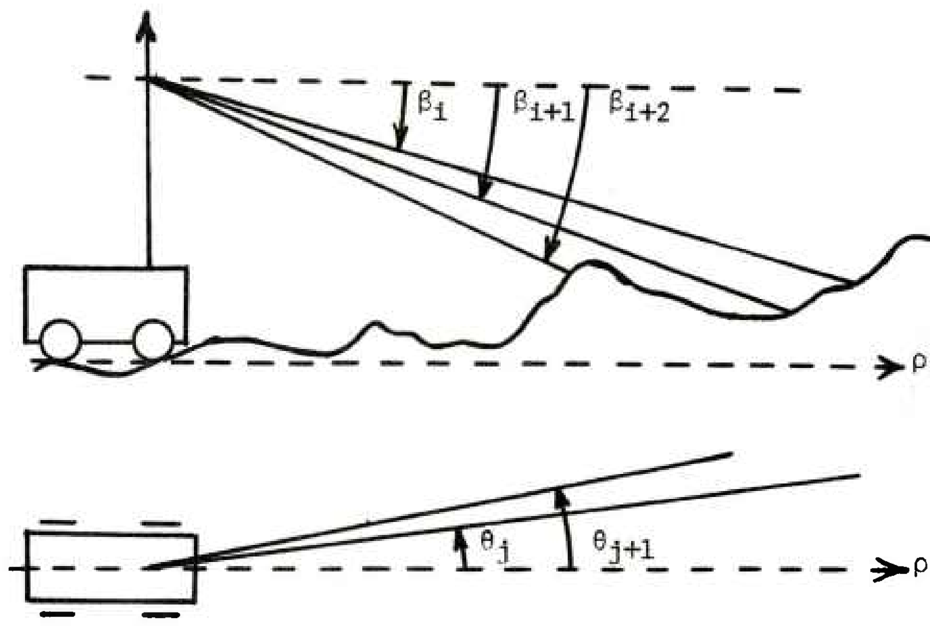

Figure 1. Top and side view of a rangefinder.

If x_i represents the true range, then z_i (the j subscript is dropped from now on since it remains fixed for a given column processing) is given by:

$$z_i = x_i + v_i \tag{1}$$

in which v_i is added measurement noise assumed to be white and Gaussian distributed with mean zero and variance R.

The equation of state for this problem is given by:

$$x_{i+1} = F_i x_i + w_i + \delta_{ik} u_k \tag{2}$$

in which

$$F_i = \frac{\sin\beta_i + \tan\eta_i \cos\beta_i}{\sin\beta_{i+1} + \tan\eta_i \cos\beta_{i+1}} \text{ for column processing;} \tag{3}$$

η_i = slope of the plane (terrain) near point i;

w_i = system noise such as terrain noise which is assumed white and Gaussian distributed with mean zero and variance Q; and

u_k = impulsive jump in the range at point k caused by presence of an object.

In Eq. (2), x_{i+1} represents the range for elevation angle β_{i+1}, and can be estimated from information prior to point i+1. In the computer algorithm η_i is determined adaptively using ranges near and prior to point i.

Standard Kalman filtering is used to obtain estimates of the ranges from the measured data if no impulsive input is detected where $\hat{x}_i$ and P_i are the estimate and error covariance at point i:

Prediction:

$$\bar{x}_{i+1} = F_i \hat{x}_i \tag{4}$$

$$M_{i+1} = F_i^{\,2} P_i + Q_i \tag{5}$$

$$= \text{variance of the error in } \bar{x}_{i+1}$$

Kalman Gain:

$$K_{i+1} = M_{i+1}(M_{i+1}+R_{i+1})^{-1} \tag{6}$$

Correction:

$$\hat{x}_{i+1} = \bar{x}_{i+1} + K_{i+1}(z_{i+1}-\bar{x}_{i+1}) \tag{7}$$

$$P_{i+1} = (1-K_{i+1})^2 M_{i+1} + K_{i+1}^{\,2} R_{i+1} \tag{8}$$

For the case in which no prior data is included such as when first starting the column processing or immediately after a jump is detected, then $\hat{x}_i$ and P_i are estimated directly as z_i and R_i.

DETECTION OF OBJECT EDGES

In stepping through each point i of the range vector, a decision must be made as to whether or not an impulse (e.g. object edge) is present between points i and i+1. This is accomplished by setting up a number of hypotheses and then applying a decision rule to determine which hypothesis is most probable, given the data. Essentially, the measured ranges are statistically compared to predicted ranges assuming no impulse. The hypotheses considered are listed as follows:

H_1 - impulsive input exists between points i and i+1

H_2 - impulsive input exists between points i+1 and i+2

H_3 - impulsive input exists between points i+2 and i+3

H_4 - no input exists between points i and i+3

The motivation for considering the states at the three forward points is to improve reliability of the decision process (see Reference 4 for discussion of this approach).

A Bayesian decision rule (ref 6) is then applied to the hypotheses and the hypothesis with lowest Bayes' risk determined. If H_1 is not chosen, then the range at i+1 is estimated using Eqs. (4) through (8) and the entire decision process is repeated at this next point.

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[4]Kim, C. S., Marynowski, R. C., and Shen, C. N., "Obstacle Detection Using Stabilized Rapid Estimation Scheme With Modified Decision Tree," Proc. of JACC, Philadelphia, PA, October 1978.

[6]Sage and Melsa, <u>Estimation Theory With Applications to Communications and Control</u>, McGraw-Hill, New York, 1971, Chapter 5, "Decision Theory."

If H_1 is chosen, the location of the detected edge is stored along with other pertinent information. Then the range estimates $\hat{x}_{i+1}$ and P_{i+1} are set equal to the measured range z_{i+1} and R, respectively, and the process is reinitiated and continued until the entire vector of ranges is processed.

The conditional probabilities of the measured data given the hypotheses are used to compute the Bayes' risk B_ℓ for the ℓth hypothesis:

$$B_\ell = \sum_{k=1}^{4} p_k c_{\ell k} F(Z|H_k) \; ; \; \ell = 1,2,3,4 \qquad (9)$$

in which p_k = prior probabilities for hypothesis k;

$c_{\ell k}$ = cost associated with choosing H_ℓ when actually H_k is correct;

$F(Z|H_k)$ = conditional probability density of range measurements Z given H_k is true.

In Eq. (9) the hypothesis H_ℓ is chosen which minimizes Bayes' risk B_ℓ. The densities $F(Z|H_k)$ are given as follows:

$$F(Z/H_k) = \prod_{n=1}^{3} \frac{1}{\sqrt{2\pi}\, |W^k{}_n|^{1/2}} \exp\{- \frac{1}{2} J^k{}_n\} \qquad (10)$$

in which

$J^k{}_n = (z_{i+n} - \bar{x}^k{}_{i+n})(W^k{}_{i+n})^{-1}(z_{i+n} - \bar{x}^k{}_{i+n})$

$W^k{}_{i+n} = M^k{}_{i+n} + R_{i+n}$

$\bar{x}^k{}_{i+n}$ = predicted range at point i+n based on cumulated information at point i+n-1 for the kth hypothesis.

In Eq. (10) if an impulse is assumed to have occurred just prior to point i+n, then $\bar{x}^k{}_{i+n}$ is set equal to z_{i+n}. For more details on the derivation of Eq.

(10), see Reference 3.

SIMULATION STUDIES OF RES

The object detection procedure described in the previous sections has been extensively tested using simulation techniques. In these simulation studies, artificial scenes are created using computer routines. A range matrix is generated which contains known measurement and system noise using a random number generator. In these studies, the RES procedure worked quite efficiently in locating the edges of various kinds of objects setting on or within a given sloped plane. The main problems encountered were difficulties in (1) minimizing false alarms where a false alarm occurs when a detection is made at a point where no object input exists; (2) fixing the Bayes' prior probabilities and cost factors in Eq. (9); and, (3) determining effect of parameters on minimum detectable object size. These problems are interrelated and were studied using Monte Carlo simulation in which the main goal was to characterize the minimum object size that can be detected as a function of model parameters.

False Alarm Rate

Kim et al (ref 4) in their studies of the RES procedure, which used a two-term state vector (range and slope), fixed the Bayes' parameters. They then minimized false alarms by adding artificial system noise covariance to

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[3] Sanyal, P., "Rapid Estimation of States by Detecting Unknown Impulse Inputs at Unknown Times," PhD Thesis, Rensselaer Polytechnic Institute, Troy, NY, University Microfilms, Ann Arbor, MI, 1973.
[4] Kim, C. S., Marynowski, R. C., and Shen, C. N., "Obstacle Detection Using Stabilized Rapid Estimation Scheme With Modified Decision Tree," Proc. of JACC, Philadelphia, PA, October 1978.

their model. This is a common ad hoc procedure for handling unmodeled inputs (ref 7).

For our study, a series of Monte Carlo runs was conducted using the RES procedure described by Eqs. (1) through (10) assuming a flat plane containing no objects. In this case any detection experienced would be a false alarm. The parameters that were varied included the addition of artificial noise covariance to both the system and measurement noises R and Q and the Bayes' parameters.

A number of assumptions were made to reduce the 20 Bayes' parameters in Eq. (9) to a single parameter. The only hypothesis that has any consequence at a given point i is H_1. If H_1 is accepted as true, then a detection is concluded and recorded with the filtering-decision procedure being reinitiated at the next point. If H_2, H_3, or H_4 is accepted as true, nothing is done other than continue the filtering procedure to the next point. It will be assumed then that the prior probabilities and costs for H_2, H_3, and H_4 are equal but different from H_1:

$$p = p_2 = p_3 = p_4 \neq p_1 \tag{11}$$

The cost parameters $c_{\ell k}$ associated with choosing H_ℓ when actually H_k is correct are assumed to be:

$$\begin{aligned} c_{\ell k} &= 0 \quad \text{for } \ell = k \\ &= c_1 \text{ for } k = 1 \text{ and } \ell = 2,\ 3, \text{ and } 4 \\ &= c \quad \text{for } \ell \neq k,\ k = 2,\ 3, \text{ and } 4,\ \ell = 1,\ 2,\ 3, \text{ and } 4 \end{aligned} \tag{12}$$

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[7]Jazwinski, A. H., Stochastic Processes and Filtering Theory, Academic Press, New York, 1970, Chapter 8.

The values of p, p_1, c, and c_1 affect the RES procedure only as a ratio given by:

$$b = \frac{pc}{p_1 c_1} \tag{13}$$

In the flat plane case with no objects present, the range matrix was generated assuming only measurement noise of mean zero and covariance R. Artificial noise can be added to the RES procedure in multiples of this R. That is, $R(RES) = R + f_R*R$ and $Q(RES) = f_Q*R$, where the actual Q is assumed zero in these particular trials.

Some of the results of the Monte Carlo runs are given in Table I. As can be seen from Table I, there are various combinations of f_R, f_Q, and b that will yield a minimal number of false alarms for the cases considered. The next question is which combination is optimum with respect to the minimum size detectable object.

TABLE I. FALSE ALARM RATE AS A FUNCTION OF RES PARAMETERS

Artificial Noise Factors		Bayes' Ratio	False Alarm Rate, per
f_R	f_Q	b	1000 points
0	0	2	54.3
		3.5	25.0
		5	11.0
		10	3.4
		20	1.3
		50	.3
		100	0
1	0	3.5	3.0
		5	.3
		10	0
5		2	0
0	1	5	3.4
		10	.3
		20	0
0	5	10	0

Minimum Detectable Object Size

In order to study the minimum size impulse that can be detected, a number of additional Monte Carlo runs were conducted assuming the field of view to be a plane containing a series of steps, both up and down, with varying heights from run to run. The important statistic in these runs is the residual from point i to i+1. The residual is defined as

$$r_{i+1} = z_{i+1} - \bar{x}_{i+1} \tag{14}$$

where r_{i+1} represents the difference in the measured data (z_{i+1}) and the predicted range obtained from filtered data up to point i. If no impulsive input exists at i+1, then r_{i+1} should contain only measurement noise and would be relatively small. In the Monte Carlo trials, an estimate was made of the residual above which the RES procedure resulted in a detection on the average. The distribution of detections about this average appeared quite sharp from the results obtained in this study. In most cases, once the residuals passed the calculated average, a detection was always obtained. Also, the calculated average residual was found to be independent of the actual range, but dependent on measurement noise covariance R, artificial noise factors f_R and f_Q, and the Bayes' parameter b.

Table II lists the results obtained for the residual threshold estimates given as multiples of $\sigma_R = \sqrt{R}$. The results were obtained for different combinations of f_R, f_Q, and b which yielded zero or low false alarm rates as given in Table I.

From the results presented in Table II, the most efficient approach to minimizing detectable object size in terms of minimizing false alarms is to adjust the Bayesian decision criteria. The least efficient approach is to artificially add system noise covariance. Also, further decrease in the residual threshold can be obtained if a few false alarms can be tolerated.

TABLE II. MINIMUM DETECTABLE THRESHOLD LEVELS FOR RESIDUALS

Artificial Noise Factors f_R	Artificial Noise Factors f_Q	Bayes' Ratio b	False Alarm Rate Per 1000	Residual Threshold Estimate*, r_t
0	0	100	0	3.4
1	0	10	0	3.5
5	0	2	0	3.8
0	1	20	0	4.2
0	5	10	0	5.4
0	0	10	3.4	2.6
1	0	3.5	3.0	3.0
0	1	5	3.4	2.9

*Multiples of measurement noise std. dev. σ_R

Instrument Accuracy Requirements

The results obtained in the previous sections can be used to estimate the accuracy of instrumentation, such as a laser rangefinder, required to detect objects of a given size at a given range. The required maximum instrument noise σ_{Rmax} is a function of the residual threshold estimate r_t as given in Table II, the height H of the instrument above the ground, the range ρ, and the minimum object height y_t to be detected (see Figure 2):

$$\sigma_{Rmax} = \frac{y_t((H-y_t)^2 + \rho^2)^{1/2}}{r_t(H-y_t)} \tag{15}$$

Equation (15) is derived by considering only geometric relationships of the various quantities involved as shown in Figure 2. As an example, let H = 2 meters, ρ = 20 meters, and y_t = 0.05 meters. From Table II, choose r_t to be 3.4 ($f_R = f_Q = 0.0$, b = 100). This gives a required σ_{Rmax} = 0.15 meters.

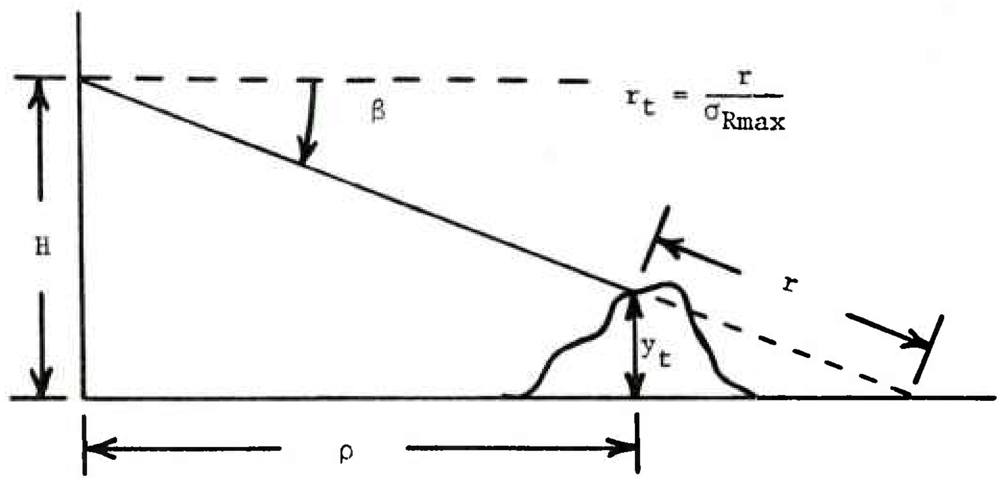

Figure 2. Geometrical relationship of residual r to model parameters.

CONCLUSIONS

The RES procedure presented as Eqs. (1) through (10) provides a fast and efficient computer technique for object detection based on range data measurements. The results presented show minimum object size that can be detected as a function of false alarm rate, Bayesian decision criteria, measurement noise level, and covariances of artificial noise levels. Results indicate that the most efficient approach to minimizing false alarms in terms of minimizing detectable object size is to adjust the Bayesian decision criteria. The least efficient approach is to artificially add system noise covariance.

Much work remains to be done on assessing available laser rangefinders to determine if achievable accuracies against non-standard targets with varying reflectivity fall within required accuracies. The required accuracies can be roughly estimated from the results presented in this report given the required range and minimum object sizes to be detected.

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NOTE: PLEASE NOTIFY COMMANDER, ARMAMENT RESEARCH AND DEVELOPMENT CENTER, US ARMY AMCCOM, ATTN: BENET WEAPONS LABORATORY, SMCAR-LCB-TL, WATERVLIET, NY 12189, OF ANY ADDRESS CHANGES.