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Designing a Deer Detection System Using a Multistage Classification Approach

Acceptable accuracies are obtained, in real time, for the detection of deer when using four spectral bands.

(Abstract on next page)

Introduction

Wild deer are an important economic, aesthetic and cultural resource. Reliable estimates of the deer population are required for proper management, for ascertaining allowable harvest, and for assessing environmental impacts. Many researchers (Gill, 1976; Rue, 1978; Connolly, 1981) have remarked about the economic importance of deer and the unavailability of reliable deer population estimates for North America. The research reported in this paper deals with development of tools and techniques for the remote detection of mule deer (*Odocoileus hemionus*) on winter ranges of the western United States.

A successful implementation of remote sensing methods for any problem requires that the objects of interest exhibit unique signatures. These signatures exist in the domains associated with electro-optical sensors. The three domains generally considered are spectral, spatial, and temporal (Wyatt, 1978; Landgrebe, 1981). Recent research reported by Trivedi *et al.* (1982) analyzed spectral signatures for deer and a typical habitat scene. The study indicated that deer and the most commonly occurring background objects like snow, green vegetation and brush exhibit unique spectral signatures which can be used for remotely identifying such objects. As implied in the name "remote sensing," the main advantage of such techniques is the capability to acquire relevant data from physically distant sensor platforms. Thus, the difficulty posed by the generally inaccessible terrain of natural deer habitat can be overcome. Also, such techniques can acquire data at an extremely fast rate, and proper data processing methods can make very efficient tools for animal detection.

The study based on the multispectral approach (Trivedi *et al.*, 1982) utilized a spectral range of 0.4 μm to 1.1 μm to collect reflectance data in the visible and near-infrared portion of the electromagnetic spectrum. This range was recommended by Pate (1979), from laboratory studies, as the one with the most promise for the detection of deer in natural habitat. The field experiment, in a controlled winter setting, was performed to acquire a large multispectral data set comprising the spectral response from deer, snow, green vegetation, brush, and other background objects of interest. In the experiment, the green vegetation class was represented by juniper (*Juniperus osteosperma*) and sagebrush (*Artemisia tridentata*), whereas dried brush class was represented by rabbitbrush (*Chrysothamnus nau-*

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ABSTRACT: *The purpose of this paper is to present a design of a prototype system for the remote detection of deer in their natural habitat. A multistage pattern recognition algorithm which satisfied the requirements of acceptable accuracy, high speed of operation, and relatively simple hardware implementation is discussed. In order to develop such an algorithm, controlled field data collected in a previous study were used. These data were acquired at a research site, in northern Utah, typical of a deer winter range in the western United States. The classifier utilized four spectral measurements corresponding to 0.672 μm, 0.725 μm, 0.764 μm, and 0.863 μm. The classifier provided a deer detection accuracy of 55.2 percent, with no false counts, in a scene comprised of snow, green vegetation, and dry brush. When the dry brush class was excluded, the accuracy increased to 87.6 percent, with no false counts. These results compared favorably with those obtained by using a more complex single stage Bayesian classifier (Trivedi et al., 1982). A hardware implementation of the multistage classifier, which generated the deer counts in real-time, was presented. Also, the preliminary results of such a prototype system in a field situation were discussed. These results seem to be quite promising, and further studies involving more realistic testing were recommended.*

seosus). The field data were used to formulate and apply measurement selection and Bayesian classification algorithms to assess the feasibility of deer detection. The study recommended wavelengths of 0.672 μm, 0.725 μm, 0.764 μm, and 0.981 μm for a prototype system. It was shown that, by increasing the number of spectral bands from three to four, the deer detection probability increased from 49.5 percent to 57.0 percent. For the case where the scene was free of dried brush, a remarkable improvement in the probability of deer detection was observed; here a three band classifier provided 75.7 percent and four band classifier provided 84.1 percent accurate results. Such a case corresponds to a situation after a fresh snow-fall has covered low lying basal stems. This study made a positive recommendation regarding the development of a prototype system for deer detection.

Once the feasibility of a remote sensing approach for deer detection was theoretically justified, the next step was to develop data analysis algorithms which can be implemented in a practical prototype system. The main requirement for such algorithms was that they should be able to identify scene elements at an extremely fast rate, i.e., within a few microseconds. A typical aircraft sensor which might be used in animal population surveys would be looking at a new scene element every few microseconds. Because the size of the scene elements is extremely small, on the order of 125 by 125 mm, storage of such data for a complete mission is practically impossible. Also of importance is the factor related to the complexity of hardware realization of such an algorithm. One would like to make the "Deer Detection Device" as simple as possible, a device which can be realized at a reasonable cost without sacrificing the prescribed accuracy and reliability. It was, therefore, necessary to examine algorithms which could process and analyze the information in a real-time fashion and whose hardware implementation would not be excessively complex.

The objective of the research reported here was to develop an algorithm for the detection of deer which meets the prototype requirements of accuracy, high speed of operation, and relatively simple hardware design. Such an algorithm can be implemented directly using high speed hardware components. The multistage classification procedure developed utilized the ratios of the spectral bands corresponding to 0.672 μm, 0.725 μm, 0.764 μm, and 0.863 μm. Favorable results of the study prompted a hardware implementation of the classification procedure. Preliminary results acquired with the prototype system seem to be as predicted by the computer studies and appeared promising.

METHODS

As mentioned earlier, a multivariate Bayesian classification procedure that provided acceptable accuracy for the remote detection of deer was used by Trivedi *et al.* (1982). It will be shown in this section that, although such a technique is accurate and theoretically sound, it is not very efficient for implementation in an operational system. The analysis reported here was based on the same data set that was used for the development of the Bayesian classification procedure for deer detection. It was, therefore, possible to compare the results reported in the references with those acquired in this study.

DATA DESCRIPTION

The multispectral data in 0.4- to 1.1-μm range were collected with a circular variable filter spectrometer at a research site located in Logan, Utah. The site was quite typical of winter deer range in the western United States. The experiment was conducted over a period of approximately five weeks in the months of January and February, 1978. The main reason for choosing the winter time for such an experiment was that during winter the deer population is concentrated in open areas with shrub growth, upon south facing slopes with little overhead tree cover. Also, in the winter most of the background is covered with snow, and snow exhibits a unique spectral signature. The scene was considered to be one which included deer, green vegetation, and dormant brush with a background of snow. Juniper and sagebrush, a major deer browse and a dominant shrub on many winter ranges, were used to typify green vegetation. Rabbitbrush class was included to represent partially defoliated dormant brush. Thus, each measurement run consisted of the radiant flux measurements of samples from five classes: deer, snow, juniper, sagebrush, and rabbitbrush. The spectrometer was located on a 15-foot tower, which provided an overhead angle of elevation for the spectral measurements. The field-of-view of the spectrometer covered only the object of interest, and any averaging of target and background was avoided. Additional details of the field experiment are presented in Trivedi (1979) and Trivedi *et al.* (1982).

The data were recorded in analog form and later converted into digital form. The digitized scan data were processed to provide for discrete spectral bands which correspond to the resolution of the spectrometer. Each digitized scan was characterized by fifty discrete spectral bands (measures).

Extensive measurement selection and classification studies using this data set had shown that wavelengths 0.672 μm, 0.725 μm, 0.764 μm, and 0.981 μm provide best results for the deer detection problem (Trivedi *et al.*, 1982). Also, it was observed that spectral bands corresponding to 0.603 μm and 0.863 μm offered useful discriminatory information. Therefore, in this research the above six measures with a total of 525 multispectral data samples (105 of each of the 5 classes) were examined.

COMMENTS ABOUT BAYESIAN CLASSIFICATION APPROACH

The objective of a classification procedure is to identify the spectral measurements as associated with either deer or one of the "not-deer" objects like snow, green vegetation, or brush. One would like to perform such a classification as accurately as possible. The Bayesian classification procedure allows us to classify the data such that the overall probability of error is minimized (see Duda and Hart (1973), Tou and Gonzalez (1974), Devijver and Kittler (1982) where the complete development of Bayesian classification procedure is presented). Trivedi *et al.* (1982) have utilized such a procedure. Their formulation utilized normalized measures derived from the uncorrected flux measurements in various spectral bands. It was observed that the magnitude of the measurement vectors was dependent to a great extent on the illumination conditions. However, the angular specifications of the vectors, given by their direction cosines, corresponded to the spectral properties of the scene (the direction cosine measurements are discussed in the following section). Therefore, the classification procedure utilized the direction cosines as the normalized measures.

The hardware implementation of such a detection scheme would require a system similar to that shown in Figure 1. Let M_1, M_2, M_3, and M_4 represent the spectral measurements made by four detectors, each corresponding to an appropriate spectral band. The first block processed these measurements to compute the direction cosines. The decision function, d_i, corresponding to class ω_i was derived by performing the following computation:

$$d_i = -\tfrac{1}{2}\ln|\hat{\boldsymbol{\Sigma}}_i| - \tfrac{1}{2}\{(\mathbf{X} - \hat{\boldsymbol{\mu}}_i)^{\mathrm{T}}\,\hat{\boldsymbol{\Sigma}}_i^{-1}\,(\mathbf{X} - \hat{\boldsymbol{\mu}}_i)\} + \ln P(\omega_i),\ i = 1, \ldots, c$$

where $\mathbf{X}$ = measurement vector in R^4,
$\hat{\boldsymbol{\mu}}_i$ = estimate of the mean vector for class ω_i,
$\hat{\boldsymbol{\Sigma}}_i$ = estimate of the covariance matrix for class ω_i,
$P(\omega_i)$ = *a priori* probability for class ω_i, and
c = number of classes in the scene.

It should be noted that the above computation involves matrix subtractions and multiplications and scalar additions and subtractions. This form can be rearranged to make it somewhat simpler for evaluation, but even in such simplified form matrix multiplication and scalar additions are required. Also, this approach requires the storage of the value for each covariance matrix determinant, their inverses, mean vectors, and *a priori* probabilities for each class which were described in the training. Finally, the last block in the system compared these decision functions and classified the vector, **X**, to the class corresponding to the largest decision function value. The operational system requires only the deer counts and, therefore, a counter can be incremented by the signal generated on the line indicated as deer.

MULTISTAGE CLASSIFICATION: APPROACH AND DESIGN

Approach. The problems associated with the hardware implementation of the decision procedure, described above, can be alleviated by considering a multistage approach. The following definitions are useful for later discussions:

Single stage classification: A classification procedure where all available measures are simultaneously uti-

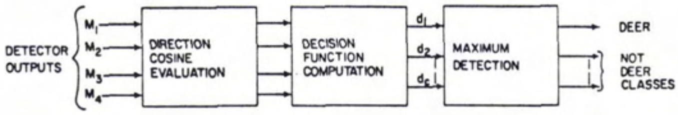


FIG. 1. Single stage, four measure classification scheme.

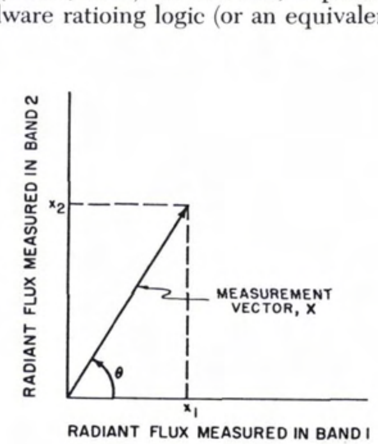
lized to evaluate the decision boundaries for classification.

Multistage classification: A classification procedure where different sets of measures are utilized to make several "sub-decisions," leading to the final classification.

The Bayesian decision procedure discussed earlier was a single stage classification method. The ultimate goal of any scheme is to classify the scene into the appropriate classes. The main advantages for considering a multistage approach are

- Dimensionality Considerations: In the pattern recognition literature it is a well known observation that by increasing the dimensionality of the measurement space one does not necessarily improve the classification accuracy. In fact, in most real world situations the classification accuracy deteriorates as additional measures are considered (Duda and Hart, 1973). This effect is mainly due to the finite sample size used in the training of the classifier. A commonly used engineering rule of thumb is to use enough training samples so that the ratio of number of samples to the dimensionality of the measurement space is at least ten (Foley, 1972; Swain, 1978). In a single stage classification, all the measures useful for discrimination of two particular classes may not be so useful for some other classes. Therefore, eventually in single stage classification one tries to include a large number of measures. In multistage classification, on the other hand, each stage can be designed so that it is useful for discriminating a smaller number of classes, and when all stages are considered globally, the scene can be classified into all the available classes. By dividing the classification task into stages, one can design each stage with a smaller number of measures, and its performance for discriminating two classes could be even better than that of a single stage classifier.
- Hardware simplicity: As mentioned earlier, individual stages in the multistage classifier require a fewer number of measures than the decision module of a single stage classifier. Generally, the more the number of measures involved in decision logic, the more complex the design becomes. Thus, a multistage classifier would require simpler hardware logic. Also, in the multistage classification scheme, each module is designed to perform a selected task most efficiently. For example, the first stage can be designed in a two-stage classifier to minimize the "miss" type errors. These are errors caused by misclassifying deer into notdeer class. The second stage can be designed to minimize the "false alarm" type errors. These are caused by misclassifying notdeer objects into the deer class. The performance of the classifier can be examined in a test environment, and the appropriate module can be adjusted to obtain the best results. In the single-stage classifier the miss and false alarm errors are generally affected simultaneously, and it is more difficult to *fine-tune* the classifier.
- Efficiency considerations: It has been shown in some studies that a classification performed by multistage classifiers, termed as "decision tree classifiers," requires a lesser number of calculations than the single-stage classifier (Swain and Hauska, 1977; Meisel and Michalopoulos, 1973; Wu *et al.*, 1975).

Design. The previous study (Trivedi *et al.*, 1982) had found that the magnitude of the measurement vector was dependent upon the solar illumination conditions. On the other hand, the angle of the measurement vector was basically a characteristic of the spectral properties of a particular scene element. Therefore, direction cosines were used as the measures in the classification studies. Another measure of the angle made by a measurement vector is the tangent of the angle. Figure 2 illustrates that for a two-dimensional case; the ratio of the spectral measurements in the two bands corresponds to the tangent of the measurement vector in R^2. Also, any scheme that utilizes ratios of the measurements has the characteristic that it can cancel the common mode variations such as overhead illumination effects, some atmospheric effects, and/or instrument noise, etc. This observation is particularly true if the wavelengths of the spectral bands are close to each other (Slater, 1980). In addition, implementation of a hardware ratioing logic (or an equivalent thereof)



$$\theta = \cos^{-1}\left(\frac{x_1}{(x_1^2 + x_2^2)^{1/2}}\right) = \tan^{-1}\left(\frac{x_2}{x_1}\right)$$

FIG. 2. Angular specification of a measurement vector in a two-dimensional measurement space. The correspondence between the direction cosine and the arctangent of the angle θ is also shown.

is easier and more common than the implementation of direction cosine evaluation unit. Therefore, the normalized measures utilized in this research for multistage classification are ratios of spectral measurements.

Recall that the following six bands were considered as the most suitable for classifying deer: 0.603 μm, 0.672 μm, 0.725 μm, 0.764 μm, 0.863 μm, and 0.981 μm. This led to $\binom{6}{2} = 15$ possible ratios. The basic statistical properties-mean, standard deviation, and coefficient of variation-were evaluated for the 15 ratios. The inverse ratios (i.e., x_1/x_2 instead of x_2/x_1) were believed to have the same information regarding the characterization of a class. Consideration of a ratio over its inverse can be justified if it has a smaller coefficient of variation. For the data under examination, the ratios and their inverses did not produce a corresponding coefficient of variation difference of more than 3 percent. The statistical properties for the five classes are summarized in Table 1. A remark about the notation used in the paper is in order. The value of a spectral measurement corresponding to wavelength i will be denoted as $[i]$; thus, $[i]/[j]$ would represent the ratio of measurements made in the spectral bands corresponding to wavelengths i and j, respectively.

Information in Table 1, is shown graphically in Figure 3. Here D = deer, S = snow, J = juniper, Sb = sagebrush, and R = rabbitbrush. The dark dots with an identifying symbol correspond to the mean ratio value, and the horizontal lines represent ± one standard deviation spread. Note that, for the sake of clarity and brevity, only ten ratios from a total of 15 were depicted. Juniper and snow can be distinguished from other classes by several different ratios. Sagebrush and rabbitbrush were more difficult to discriminate from the deer class. By careful evaluation of coincident measure plots and the coefficients of variation, ratios [0.725 μm]/[0.672 μm], [0.863 μm]/[0.764 μm], and [0.764 μm]/[0.672 μm] were selected for further analysis. Note that the 0.981 μm wavelength, which was recommended in the previous study (Trivedi *et al.*, 1982), was not utilized; instead, the 0.863 μm wavelength was selected because the ratio computed using the measurements corresponding to the 0.981 μm wavelength were judged to be relatively noiser (as can be observed by examining the coefficients of variations given in Table 1). These ratios, for the 105 samples of all the five classes, were reported by Trivedi (1981).

The decision functions generated by the Bayesian classification scheme with the normality assumption are nonlinear in form. Actual hardware implementation of such decision functions is much more complex than that of linear decision functions. The nonlinear decision functions generate hyperellipsoids in the measurement space corresponding to each class. It is possible to simplify the design procedure significantly by approximating the hyperellipsoids by

TABLE 1. SUMMARY OF THE STATISTICAL PARAMETERS. THE RATIOS OF SPECTRAL MEASUREMENTS WERE COMPUTED USING THE TRAINING SAMPLES OF DEER, SNOW, JUNIPER, SAGEBRUSH, AND RABBITBRUSH CLASSES.

		RATIO							
		[0.672 μm]/[0.603 μm]	[0.725 μm]/[0.603 μm]	[0.764 μm]/[0.603 μm]	[0.863 μm]/[0.603 μm]	[0.981 μm]/[0.603 μm]	[0.725 μm]/[0.672 μm]	[0.764 μm]/[0.672 μm]	[0.863 μm]/[0.672 μm]
DEER	Mean	1.73	2.36	2.63	2.8	1.49	1.36	1.51	1.61
	St. Deviation	0.17	0.34	0.43	0.55	0.37	0.11	0.15	0.21
	Coeff. Var. %	9.86	14.22	16.18	19.62	24.75	8.09	10.00	12.89
SNOW	Mean	1.41	1.54	1.52	1.26	0.46	1.09	1.08	0.89
	St. Deviation	0.06	0.09	0.09	.08	0.09	0.03	0.03	0.04
	Coeff. Var. %	4.18	5.52	5.71	6.51	18.31	2.73	2.97	4.82
JUNIPER	Mean	1.21	6.71	7.89	7.39	3.04	5.57	6.56	6.13
	St. Deviation	0.11	0.74	0.88	.93	0.61	0.81	0.96	0.94
	Coeff. Var. %	9.07	10.96	11.15	12.57	20.2	14.45	14.63	15.39
SAGEBRUSH	Mean	1.59	2.65	2.92	2.82	1.32	1.67	1.84	1.77
	St. Deviation	0.09	0.27	0.35	0.41	0.29	0.12	0.16	0.2
	Coeff. Var. %	5.86	10.17	12.00	14.4	21.66	7.27	8.87	11.18
RABBITBRUSH	Mean	1.62	2.3	2.5	2.37	1.06	1.42	1.55	1.46
	St. Deviation	0.12	0.21	0.26	0.31	0.22	0.09	0.11	0.13
	Coeff. Var. %	7.41	9.11	10.39	13.14	20.53	6.33	7.36	8.88

		RATIO						
		[0.981 μm]/[0.672 μm]	[0.764 μm]/[0.725 μm]	[0.863 μm]/[0.725 μm]	[0.981 μm]/[0.725 μm]	[0.863 μm]/[0.764 μm]	[0.981 μm]/[0.764 μm]	[0.981 μm]/[0.863 μm]
DEER	Mean	0.86	1.11	1.18	0.63	1.06	0.56	0.53
	St. Deviation	0.16	0.04	0.09	0.10	0.06	0.08	0.06
	Coeff. Var. %	19.13	3.27	7.72	15.87	5.61	14.40	10.66
SNOW	Mean	0.34	1.00	0.82	0.31	0.83	0.32	0.38
	St. Deviation	0.06	0.02	0.03	0.06	0.03	0.06	0.06
	Coeff. Var. %	18.64	1.50	3.64	18.27	3.36	18.1	15.61
JUNIPER	Mean	2.53	1.18	1.1	0.45	0.94	0.38	0.41
	St. Deviation	0.56	0.03	0.05	0.06	0.04	0.05	0.04
	Coeff. Var. %	22.15	2.37	4.68	13.89	3.82	13.23	10.49
SAGEBRUSH	Mean	0.83	1.10	1.06	0.45	0.96	0.49	0.46
	St. Deviation	0.16	0.03	0.06	0.06	0.04	0.07	0.05
	Coeff. Var. %	19.28	2.74	5.35	13.00	3.63	14.01	10.85
RABBITBRUSH	Mean	0.65	1.09	1.03	0.46	0.95	0.42	0.44
	St. Deviation	0.11	0.03	0.06	0.07	0.04	0.06	0.05
	Coeff. Var. %	16.7	2.63	5.72	15.06	4.2	14.25	11.06

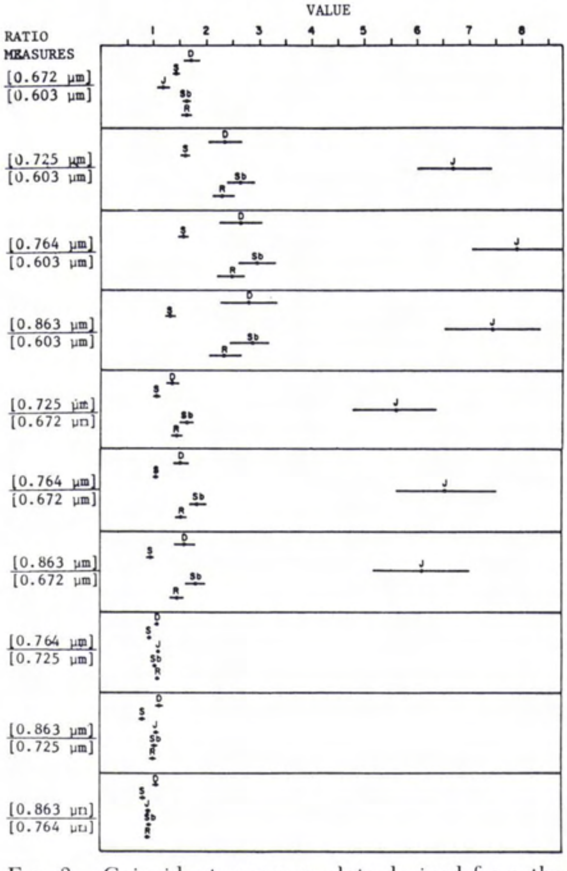


FIG. 3. Coincident measure plots derived from the training samples of the five classes. In this, D = deer, S = snow, J = juniper, Sb = sagebrush, and R = rabbitbrush class. The dots identify the mean ratio value and the horizontal lines represent one standard deviation spread.

appropriate parallelopoids. Here, the class boundaries in the measurement space are lineraly specified. Landgrebe (1981) has remarked that the pragmatic value of similar algorithms makes them useful in commercially available systems. As an illustration, consider the two-dimensional measurement space shown in Figure 4. Let the two axes correspond to the ratios of detector outputs; then the problem of deer classification can be stated: whenever the detector outputs produce a vector falling in the shaded region, it signifies detection of a deer.

A two-stage classification scheme can be implemented as shown in Figures 5a and 5b. Figure 5a represents a two-stage parallel realization of the classifier. The upper stage detects points falling between the threshold values of $(T_1)_{\mathrm{Min}}$ and $(T_1)_{\mathrm{Max}}$ for the M_2/M_1 ratio, whereas the lower stage detects pixels that fall between the $(T_2)_{\mathrm{Min}}$ and $(T_2)_{\mathrm{Max}}$ thresholds for the M_4/M_3 ratio. A deer count pulse is generated whenever constraints imposed by both stages are satisfied.

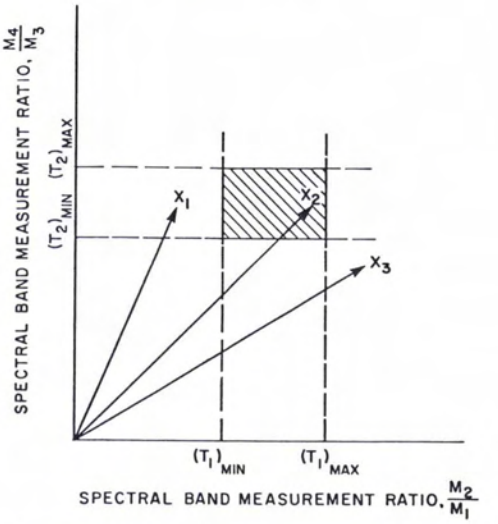


FIG. 4. Decision boundaries in a two-dimensional measurement space. Measurement vector falling in the shaded region is labeled as deer. Thus, vectors X_1 and X_3 correspond to nondeer samples, whereas X_2 represents a deer sample.

Figure 5b illustrates a serial realization of the two-stage classifier. Notice that stage two is not enabled until the stage one constraint is satisfied. This realization may be slower than that of Figure 5a, but a possible advantage is that the second stage is activated for a small fraction of the time that stage one is in operation. If stage one is designed to discriminate deer from snow and juniper and stage two to discriminate deer from sagebrush and rabbitbrush, then it is possible that stage two will be operational for approximately 1 to 5 percent of the time that stage one is in operation, because most of the background objects are snow and juniper on a winter range.

RESULTS

The suitability of a multistage classifier for a deer detection system was evaluated by performing several experiments. A description of these experiments and their results is presented in this section. Also, a hardware design for a prototype system is discussed, and preliminary results acquired in a field study are presented.

For the purposes of designing a deer detection system, the following two criteria were considered important:

- the classifier decision-making scheme should maximize the probability of deer detection, and
- the probability of false alarms, due to not-deer objects being incorrectly called deer, should be minimized.

It should be noted that, in an operational system, detection of a deer pixel by the sensor is a rather

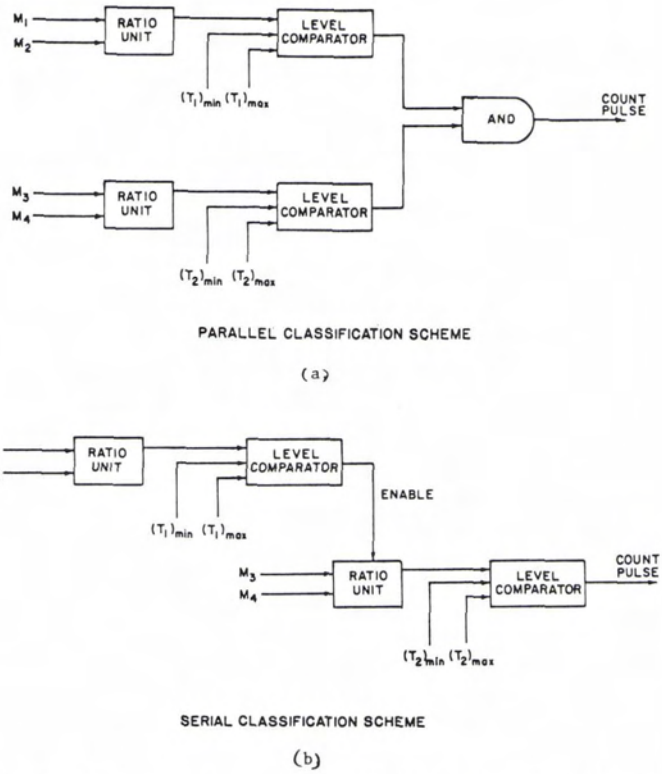


FIG. 5. Two-stage classification schemes. (a) represents a parallel implementation, whereas (b) shows a serial implementation for the same classification task.

rare event, i.e., most of the pixels seen would belong to background objects. Therefore, it is essential to have a very low, almost zero, false alarm error rate.

CLASSIFICATION USING FOUR SPECTRAL BAND MEASUREMENTS

Classification results of a two-stage classifier are presented in Table 2. Using the notation defined earlier the parameters used in the decision process can be summarized as:

The spectral bands were 0.672 μm, 0.725 μm, 0.764 μm, and 0.863 μm;

the ratios considered were

$$T_1 = \frac{[0.725\ \mu\text{m}]}{[0.672\ \mu\text{m}]} \text{ and } \qquad T_2 = \frac{[0.863\ \mu\text{m}]}{[0.764\ \mu\text{m}]}\text{; and}$$

the thresholds used for making the decision were

$(T_1)_{\text{Min}} = 1.29$, $\quad (T_1)_{\text{Max}} = 1.62$,

$(T_2)_{\text{Min}} = 1.041$, and $\quad (T_2)_{\text{Max}} =$ unspecified.

As shown in Table 2a, in stage one only those samples were called deer for which the ratio was greater than 1.29 and smaller than 1.62. Such a test eliminated all juniper and snow samples from further consideration. This was an important result because on a typical winter deer range approximately 90 to 95 percent of the actual scene would have either snow or green vegetation cover.

The second stage classified samples as deer for which the ratio T_2 was greater than 1.041 (Table 2b). The probability of deer detection with such a classifier was 55.2 percent with no false counts. This figure compares favorably with the 57.0 percent deer detection accuracy achieved using the more complex single stage Bayesian classifier for similar conditions (Trivedi *et al.*, 1982).

Next, consider the performance of a two-stage classifier where only four classes were included in the scene. The classes were deer, snow, juniper, and sagebrush. The rabbitbrush class, which corresponds to the dried brush on the winter range, was excluded from consideration in this experiment. This corresponds to a case soon after a fresh snowfall. The results of such experiments are presented in Table 3. The first stage, which employed the ratio [0.725 μm]/[0.672 μm], eliminated the green vegetation samples for which the value of the ratio was greater than 1.49, i.e., $(T_1)_{\text{Min}} =$ Unspecified and $(T_1)_{\text{Max}} = 1.49$. The second stage of the classifier discriminated deer from the snow and remaining four sagebrush samples. The ratio considered was

TABLE 2. (a) FIRST STAGE CLASSIFICATION USING [0.725 μm]/[0.672 μm] RATIO. SAMPLES WERE CLASSIFIED AS DEER WHENEVER THIS RATIO WAS BETWEEN 1.29 AND 1.62. (b) SECOND STAGE CLASSIFICATION USING [0.863 μm]/[0.764 μm/] RATIO. SAMPLES WERE CLASSIFIED AS DEER WHENEVER THIS RATIO WAS GREATER THAN 1.041.

			COMPUTER CLASSIFICATION			
		FIRST STAGE	DEER	NOT DEER	TOTAL SAMPLES	ACCURACY
TRUE CLASSIFICATION		DEER	81	24	105	77.1%
	NOT DEER	SNOW	0	105	105	100.0%
		JUNIPER	0	105	105	100.0%
		SAGEBRUSH	38	67	105	63.8%
		RABBITBRUSH	95	10	105	9.5%

(a)

			COMPUTER CLASSIFICATION			
		SECOND STAGE	DEER	NOT DEER	TOTAL SAMPLES	ACCURACY
TRUE CLASSIFICATION		DEER	58	23	81	71.6%
	NOT DEER	SNOW	—	—	—	—
		JUNIPER	—	—	—	—
		SAGEBRUSH	0	38	38	100.0%
		RABBITBRUSH	0	95	95	100.0%

(b)

Probability of Deer Detection = 55.2%

[0.863 μm]/[0.764 μm] and the thresholds were $(T_2)_{\mathrm{Min}} = 0.95$ and $(T_2)_{\mathrm{Max}}$ = Unspecified. The deer detection probability was 87.6 percent, with no false counts, which was better than the 84.1 percent acquired with the single-stage classifier for similar conditions (Trivedi *et al.*, 1982).

An important result about the performance of the two-stage classifier in a special case can be mentioned. It was observed that two rabbitbrush samples (out of 105 total) were quite difficult to discriminate from the deer class. (Incidentially, these samples were acquired in consecutive runs during the field experiment, which might suggest some "error" in the data acquisition.) If one allowed the false counts due to these samples, then the deer detection accuracy using different thresholds but the same decision logic would increase to 63.8 percent with 0.5 percent false alarm rate. This result highlights the utility of the simple threshold-setting decision logic of the proposed approach which would allow the fine tuning of the hardware for special requirements.

CLASSIFICATION USING THREE SPECTRAL BAND MEASUREMENTS

Additional experiments were conducted to evaluate the effect on the deer detection accuracies of utilizing only three spectral band measurements. Because elimination of a spectral band directly affects the hardware complexity of the operational system, such a study seemed important. Only a brief summary of results is presented in this subsection. Detailed results are presented in a report by Trivedi (1981).

The three spectral band measurements utilized

TABLE 3. SCENE WITHOUT RABBITBRUSH CLASS. (a) FIRST STAGE CLASSIFICATION USING [0.725 μm]/[0.672 μm] RATIO. SAMPLES WERE CLASSIFIED AS DEER WHENEVER THIS RATIO WAS LESS THAN 1.49. (b) SECOND STAGE CLASSIFICATION USING [0.863 μm]/[0.764 μm] RATIO. SAMPLES WERE CLASSIFIED AS DEER WHENEVER THIS RATIO WAS GREATER THAN 0.95

TRUE CLASSIFICATION		COMPUTER CLASSIFICATION			
FIRST STAGE		DEER	NOT DEER	TOTAL SAMPLES	ACCURACY
DEER		95	10	105	90.5%
NOT DEER	SNOW	105	0	105	0.0%
NOT DEER	JUNIPER	0	105	105	100.0%
NOT DEER	SAGEBRUSH	4	101	105	96.2%

(a)

TRUE CLASSIFICATION		COMPUTER CLASSIFICATION			
SECOND STAGE		DEER	NOT DEER	TOTAL SAMPLES	ACCURACY
DEER		92	3	95	96.8%
NOT DEER	SNOW	0	105	105	100.0%
NOT DEER	JUNIPER	—	—	—	—
NOT DEER	SAGEBRUSH	0	4	4	100.0%

(b)

Probability of Deer Detection = 87.6%.

correspond to 0.672 μm, 0.764 μm, and 0.863 μm. For a scene containing all five classes—deer, snow, juniper, sagebrush, and rabbitbrush—the first-stage classification was based upon the [0.764 μm]/[0.672 μm] ratio and the second-stage classification utilized the [0.863 μm]/[0.764 μm] ratio. A deer detection probability of 43.8 percent was achieved with no false counts. For a similar scene Trivedi *et al.* (1982) reported a detection probability of 49.5 percent using a single-stage classifier. Thus, it seems that elimination of the fourth spectral band affects deer detection more severely using the two-stage approach than the single-stage one.

For a scene without the rabbitbrush class, how-

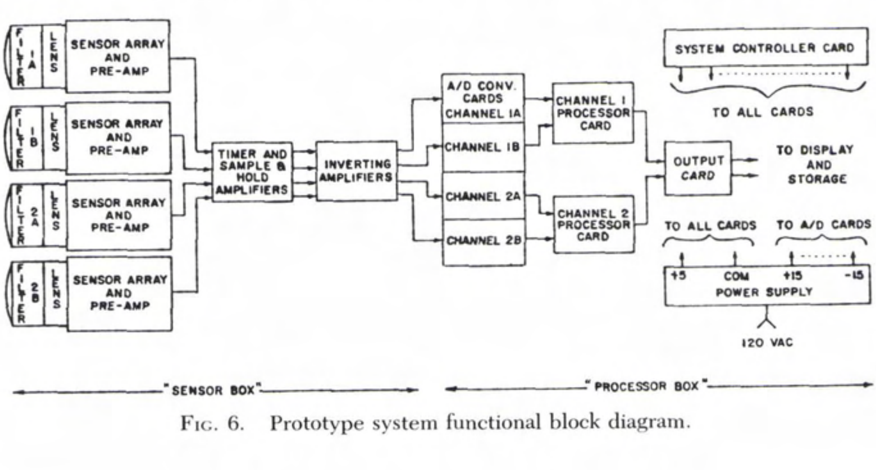


FIG. 6. Prototype system functional block diagram.

FIG. 7. Prototype system during the preparations for a field test.

ever, the same ratios as above provided a deer detection accuracy of 80.0 percent with no false counts. This figure was much better than the 75.7 percent accuracy achieved by a single-stage classifier.

OPERATIONAL PROTOTYPE: PRELIMINARY EVALUATION

The results presented above prompted a hardware implementation of the decision logic for detailed testing. The complete details of such a unit are presented by Voorheis (1982). The design was based on the following specifications:

Focal length, *f*-number	50 mm, 2.0
Aircraft altitude above ground	1330 feet
Pixel width on ground	4.8 inches
Aircraft speed	100 mph
Scan frequency	367 Hz.
Computation time per pixel	$<$1330 nanoseconds

A functional block diagram of the prototype system is given in Figure 6. The sensor box contained the band pass filters, lenses, photodiode arrays, and signal processing cards. The signals from the array boards were amplified and transmitted to the Analog-to-Digital (A/D) converter cards in the processor box. The outputs of A/D cards were paired and each pair was input to a processor card. The processing algorithm was realized using Arithmetic Logic Units (ALU), comparators, multipliers, and supporting logic circuitary. The dynamic range of the system was increased by subtracting the fixed pattern noise form the signals. Total time required by this prototype to process a pixel was 1206 nanoseconds, well within the specifications.

Preliminary tests for the prototype system were performed in field studies. In Figure 7, the system hardware is shown during the preparations of one of the tests. The deer and other background objects were placed at a distance of about 1500 feet from the sensor. The results indicated that deer detection accuracies of approximately 80 percent with false alarm rates of about 0.01 can be attained with properly selected threshold values. In preliminary tests the sensor viewed the objects from the side instead of from above, as would be the case in an operational system. This simplification in the experimental setup was done primarily due to the concerns for practicability. In order to examine the effects of the difference in viewing angle on deer detectability, further experimentation may be required. However, it is believed that, by a trial and error approach with an operational system, one can minimize any performance deterioration. The above results were promising and agreed with the results of the previous subsections. This agreement in the results of two field tests, which were conducted at an interval of about four years, could be interpreted as an indication of the consistent performance that can be obtained with the multispectral approach.

The prototype system was designed in such a way that with minor modifications some spatial domain information can be incorporated in the decision process. Future studies would address classification procedures based on the spectral-spatial information.

CONCLUSIONS AND RECOMMENDATIONS

CONCLUSIONS

Remote sensing techniques offer an attractive tool for the detection of deer in their natural winter habitat. An operational system for deer detection must satisfy the requirements of accuracy, high speed, and relatively simple hardware design. In this paper a two-stage classification scheme which meets the above requirements was developed. Each stage of such a classifier required two units: one to evaluate the ratio of the two spectral measurements and another to compare this ratio with a preselected threshold. The two stages of the classifier can be arranged in a serial or parallel mode.

The classification scheme utilized four spectral band measurements, corresponding to the 0.672 μm, 0.725 μm, 0.764 μm, and 0.863 μm wavelengths. For the five class scene, the two-stage classifier provided a deer detection accuracy of 55.2 percent, with no false counts. If the dry brush class was eliminated (such may be the case after a fresh snowfall), the deer detection accuracy increased to 87.6 percent, with no false counts. These figures compared quite well with the results reported by Trivedi *et al.* (1982), where a more complex single-stage Bayesian classification approach was utilized. The main advantages of the two-stage approach was real time processing capability and its relatively simple design. The classifier performance can be easily modified by adjusting values for the thresholds. A prototype system was designed based upon the above computer results. The preliminary results acquired with the system were promising and in agreement with the study.

RECOMMENDATIONS

The results of this study indicate a definite promise for an operational system for remote deer detection and similar applications. It should, however, be emphasized that further research is required before a final assessment for the wide spread utility of such a tool can be made. The following topics need to be addressed:

- Methods for incorporating spatial domain information in the decision process. Such information would enhance detection accuracies. Acquisition and analysis of spatial data increases the complexity of the hardware. A careful evaluation of these variables is required.
- Improvement of detection accuracies by using somewhat more involved statistical analysis techniques. Methods based on capture-recapture theory (White *et al.*, 1982) seem to offer some ways to reduce false counts while still being able to estimate the number of deer.
- Methods for handling "mixed pixel" problems need to be evaluated. This problem arises when the sensor averages pixels composed of more than one class. Statistical decision theory methods, similar to those developed for image segmentation task, might provide some insight.
- Development of a stable platform, and methods for correcting the registration errors due to the aircraft motion and vibrations.
- Methods for estimating total population size by conducting aerial surveys over selected animal habitats need to be examined. Statistical techniques based on strip transect sampling (Jolly and Watson, 1979) seem to offer an approach for the estimation task.

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