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OR Practice—Estimating Visual Detection Performance at Sea

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OR PRACTICE

ESTIMATING VISUAL DETECTION PERFORMANCE AT SEA

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This paper discusses the problem of estimating lateral range functions and sweep widths from data collected during visual detection experiments. We report a physical model for visual detection and the results of applying this methodology to data collected by the U.S. Coast Guard. These results are being incorporated in an updated version of the *National Search and Rescue Manual.*

Each year the U.S. Coast Guard is involved in many at-sea searches for lost boats, rafts, and individuals. An important part of effective search and rescue (SAR) planning is the accurate prediction of the detection performance of the SAR units. On the one hand, an underestimate of detection performance can result in an unnecessary extension of search in a particular area. On the other hand, an overestimate can produce the premature termination of search in a particular area. In both cases, the SAR resources are not being effectively used.

The primary measures of detection performance currently being employed by SAR mission coordinators are the lateral range function and sweep width. (These quantities are defined below.) The purpose of this paper is to discuss the problem of estimating lateral range functions and sweep widths from data collected during visual detection experiments. In particular, some of the difficulties involved in this estimation problem are reviewed, a candidate solution is outlined, and the results of applying this approach to Coast Guard data are reported.

The study of visual lateral range functions and visual sweep widths had its origins in the theory developed during World War II by B. O. Koopman and his colleagues in the Navy's Anti-Submarine Warfare Operations Research Group (ASWORG). Chapter 4 of Koopman (1946) provides an account of this work. In 1955, recognizing the lack of data involving small boats and rafts, the U.S. Coast Guard issued its Operations Instruction No. 58-55. This instruction required Coast Guard search and rescue units (SRUs) to file data reports "on each sighting deemed to be advantageous to the program." More than twelve thousand sighting reports were collected. However, since these reports were drawn from day-to-day operations rather than controlled experiments, there were difficulties in analyzing the resulting data. In particular, these reports provided no description of the visual detection opportunities that had failed to result in sightings. An example of the type of analysis that was performed on this data is described in Richardson (1968). The results of this and other analyses were incorporated into visual sweep width tables by the U.S. Coast Guard (1973).

In 1978, the Coast Guard initiated a series of controlled visual detection experiments in Block Island Sound and off the Florida coast. The primary objective of these experiments was to develop a solid visual detection data base that could be used to improve the accuracy of existing visual sweep width tables and to identify those physical parameters which significantly influence the visual sweep width. Edwards, Osmer, Mazour and Hover (1981) describe these experiments. The analysis of the data collected in these experiments motivates the discussion in this paper. We have developed and used a detailed, physical model (based on the work of B. O. Koopman) to estimate lateral range functions and sweep widths from the Coast Guard data. This model was originally documented in Weisinger (1984).

The results of the analysis in this paper are being used by the Coast Guard in two ways. First, this methodology is being employed to update the visual

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sweep width tables that appear in the National Search and Rescue Manual. This manual is the basic reference used by the Coast Guard in planning SAR operations. Second, a computer program that implements the estimation techniques in this paper has been delivered to the Coast Guard. As described in the final section of this paper, this program provides visual detection performance predictions when the parameters of a search problem match one of the scenarios for which data have been collected. In addition, this program will allow the Coast Guard to analyze new visual detection data as it is collected.

The discussion below is organized into three sections. The first section contains the necessary background material. In particular, it reviews concepts from the theory of search and the theory of visibility. Section 2 presents the model developed for analyzing the Coast Guard data. Finally, the third section reports the results of this analysis.

1. Background

This section provides an introduction to the problem of estimating the detection capabilities of the human eye. This discussion has three parts. First, the lateral range function is defined and its use in search planning is illustrated. Next, several important quantities from the theory of visibility are introduced. Finally, as motivation for the discussion in Section 2, the difficulties encountered in using empirical lateral range functions are outlined.

Lateral Range Functions

Consider a stationary target and a searcher in motion along a straightline track. The distance along the line segment drawn through the target and perpendicular to the searcher's track is called the *lateral range*, r, of the target from the searcher. Suppose that the probability of the searcher detecting the target while heading along a straightline track depends only on the lateral range. Then one can define $\mathrm{L}(r)$, the probability of detecting the target along a track having lateral range r. Note that this definition assumes that the searcher makes a complete pass by the target. The function L is called the *lateral range function* for the searcher. Naturally, L depends on many factors including the searcher, the target, and the environment.

The *sweep width*, W, of the searcher is defined to be twice the integral of the lateral range function.

$$W = 2 \int_0^\infty \mathrm{L}(r)\, dr. \tag{1}$$

Here, the factor of 2 before the integral reflects the fact that the target may fall on either side of the searcher's path.

As a simple example of these definitions, consider a "cookie-cutter" sensor with detection range R. This is a sensor that can detect the target with probability 1 if the target is within range R and cannot detect the target if the range is greater than R. A searcher equipped with such a sensor will have a lateral range function given by

$$\mathrm{L}(r) = \begin{cases} 1 & \text{if } r \leq R \\ 0 & \text{if } r > R. \end{cases}$$

The sweep width of this searcher is $2R$.

A standard application of the lateral range function and sweep width occurs in the planning of a parallel path search. In this search tactic, the searcher moves along a series of parallel tracks near the suspected target location. The central problem in planning such a search is determining the spacing between the search tracks. Avoiding gaps and overlaps in search coverage is particularly important when the target must be found quickly—and this is always the case with a person in the water. In practice, the track spacing in a parallel path search is often taken to be the sweep width of the searcher. Note that in the special case where the searcher's detection capability resembles a cookie cutter sensor, this choice of spacing yields complete coverage of the search region.

More detailed discussion of the lateral range function can be found in Koopman (1946, 1980), and Stone (1975).

Visual Search

Many laboratory experiments have been performed to find the primary factors that determine a human observer's ability to detect a distant object with the naked eye. Of the many variables that play a role, the following three are particularly important.

- The intrinsic contrast of the target against its background.
- The meteorological visibility.
- The visual angle subtended by the target.

These quantities are defined below.

In order for an object to be recognizable to the human eye, it must have a perceptively different luminance (brightness) or color than its surroundings. In fact, contrasts in luminance are much more important than contrasts in color. This observation is quantified by the concept of intrinsic contrast. Suppose that an isolated target is surrounded by a fairly uniform and extensive background. Let B and B' denote the luminances of the target and its background. Then the *intrinsic contrast*, Co, is given by

$$\text{Co} = 100 \left| \frac{B - B'}{B'} \right| . \tag{2}$$

Thus, intrinsic contrast can assume values from 0 to $+\infty$. A bright light shining in the darkness can achieve a very high intrinsic contrast. However, in the daylight, it is rare for an object to have an intrinsic contrast higher than 1,000.

The intrinsic contrast takes into account many environmental factors. For example, the elevation and azimuth of the sun affect the luminances of both the target and its background. Perhaps less obviously, in operations at sea the wind speed and the sea state also affect Co because both of these factors influence the formation of white caps (and hence, the value of B').

When an observer is viewing a distant object, the contrast actually perceived by the eye (called the *apparent contrast*) is often much less than the intrinsic contrast defined in (2). This decrease in contrast is due to atmospheric haze. One measure of this haze is the *meteorological visibility*. Originally, the meteorological visibility was defined as the maximum distance at which mountains on the horizon could barely be seen. This rather subjective definition has since been updated so that the meteorological visibility, V, is now the distance at which the apparent contrast, C, is precisely 2.0% of the intrinsic contrast, Co. Using this definition, research has shown that V, C, Co and R, the range of the target from the observer, can be linked through the relationship

$$C = \text{Co} \exp(-3.91R/V). \tag{3}$$

The third important factor in visually detecting a target is its size. More precisely, the apparent area of the target is defined to be the area of the projection of the target onto a plane perpendicular to the observer's line of sight. In practice, the apparent area, A, is often obtained from h, the altitude of the observer, A_H, the horizontal cross-sectional area of the target, and A_V, the average vertical cross-sectional area of the target, through the estimate

$$A = hA_H/R + A_V(1 - (h/R)^2)^{1/2}. \tag{4}$$

Once the apparent area is known, the visual angle may be computed. The *visual angle* is the angle subtended at the eye of the observer by the diameter of a circle with the same apparent area as the target. If the visual angle is measured in minutes, the apparent area in square feet, and the range in nautical miles, then the visual angle, α, is given by

$$\alpha = 0.64\sqrt{A}/R. \tag{5}$$

Further discussion on the theory of visibility can be found in Middleton (1952) and Duntley et al. (1964). The relationship in (3) is described in Duntley (1948); the expression in (5) is obtained in Koopman (1946).

The Problem

The central problem discussed in this paper is the estimation of lateral range functions for visual search. In order to understand the issues at stake in this problem, it is useful to begin by reviewing the shortcomings of one particularly straightforward approach. This approach is the construction of empirical lateral range functions.

Empirical lateral range functions are constructed as follows. Visual detection data is collected; a bin size s is selected; and the data are sorted into bins according to lateral range. Here, each piece of data is a visual detection opportunity. If the observer in a given opportunity achieves a lateral range r, then this piece of data is assigned to the nth bin where n is the integer part of $1 + r/s$. Let p_n denote the ratio of the number of visual detections to the total number of opportunities in bin n. Then, the empirical lateral range function is defined to have the value p_n on the interval $[(n - 1)s, ns]$. If the nth bin has no data, then the function is defined to be zero on the corresponding interval.

One immediate difficulty in constructing empirical lateral range functions is the selection of the bin size s. If too large an s is chosen, then the resulting function will be too coarse to reflect the actual shape of the underlying lateral range function. If too small an s is chosen, then individual bins may have too few pieces of data to estimate adequately the ratio p_n.

A second difficulty in the use of empirical lateral range functions is the restrictions that this technique places on the data. Ideally, each piece of data must record a complete straightline track of the observer. In practice, the available tracks are often not straight and occasionally they provide only partial passes of the target (that is, they do not begin and end outside the detection range). Thus, potentially useful data must frequently be discarded.

A third drawback in this approach is the lack of an underlying physical model. This leads to difficulties in two areas: organizing the data and extrapolating the results. It seems reasonable that there should be different lateral range functions for different applications (for example, a "good weather function" and a "bad weather function"). However, since there is no underlying physical model, there are no clear guidelines on how the data should be organized into groups so that an empirical function can be generated for each group. After the estimation procedure has been completed, the lack of an underlying model means that there is no natural mechanism for extrapolating the results to environments for which no data are available.

These shortcomings of empirical lateral range functions provide the motivation for using the model of Section 2.

2. Theory

This section has two objectives. First, it presents an approach to estimating a lateral range function for visual search. This approach is based on a physical model for visual detection which we call "the detection lobe model." A maximum likelihood technique described below allows this model to generate estimates of lateral range functions from visual detection data.

The detection lobe model requires us to accept specific descriptions for the detection capabilities of the human eye. Just as a touchstone is used to test the genuineness of gold or silver, it is natural that we should seek a simple "touchstone model" to test the value of this more sophisticated model. In other words, we seek an estimation technique that is reliable, but involves fewer detailed assumptions than the physical model. This technique will not be expected to address all of the difficulties outlined in Section 1, but it should provide a means for evaluating the detection lobe model. The second objective of this section is to present our touchstone model which is a nonparametric technique based on the Pool Adjacent Violators (PAV) algorithm.

In order to avoid any misunderstandings in the discussion that follows, we wish to emphasize that our use of the term "touchstone model" does not imply, in any sense, that the estimates provided by this model constitute the true underlying values of the visual sweep width. We are simply introducing this model as a straightforward and easily understandable baseline against which we can judge our more detailed physical model. After we have evaluated the physical model, the touchstone model will be discarded.

The Detection Lobe Model

Extensive research has been done to experimentally determine the region that can be seen by a human eye at a given instant. For example, such work is documented in Blackwell (1946). This work shows that if a target is θ degrees from the line of sight and if it subtends a visual angle of α minutes, then the threshold contrast C_T necessary to provide a 50% probability of detection is

$$C_T = \begin{cases} 1.75\sqrt{\theta} + \dfrac{19\theta}{\alpha^2} & \text{if } 90 \geq \theta \geq 0.8 \text{ degrees} \\ 1.565 + \dfrac{15.2}{\alpha^2} & \text{if } 0.8 \geq \theta \geq 0 \text{ degrees.} \end{cases} \tag{6}$$

Equation 6 is purely empirical. The same visual detection experiments show that this threshold contrast is a sharp threshold. In other words, a target becomes quite visible when its contrast is above C_T, while it becomes virtually impossible to see if its contrast drops below C_T.

Equation 3 describes the apparent contrast C of a target. By setting C equal to C_T, it is possible to solve for the maximum angle from the line of sight at which the observer has a 50% chance of seeing a target with given values of range, R, meteorological visibility, V, intrinsic contrast, Co, and visual angle, α. Denote this angle by $\theta_0(R)$. (Here we suppress the dependence on V, Co, and α.)

For typical values of V, Co, and α, Figure 1 shows the polar plot of the equation $\theta = \theta_0(R)$. Borrowing a term from radar and sonar, the region inside this curve is called the *detection lobe*. It can be thought of as attached to the eye and moving with it. If a target falls within this lobe at a given time, then the target is likely (in some probabilistic sense) to be detected.

To make this more precise, the detection lobe model assumes that the instantaneous rate of detection against a target at range R is proportional to $\theta_0(R)$. If detection opportunities in disjoint time intervals are independent events, then this instantaneous detection rate can be used to compute the probability, P, of detecting the target during some time interval $[s, t]$. In fact,

$$P = 1 - \exp\left(-k \int_s^t \theta_0(R(u))\, du\right). \tag{7}$$

Here, $R(u)$ is the range from the observer to the target at time u, and k is the (unknown) constant of proportionality included in the instantaneous detection rate.

In terms of the detection model given by (7), the problem of estimating lateral range functions is reduced to the problem of estimating the constant k. A maximum likelihood estimator for k is obtained as follows. Suppose that a data set is available with N searcher/target encounters. Let s_i and t_i denote the

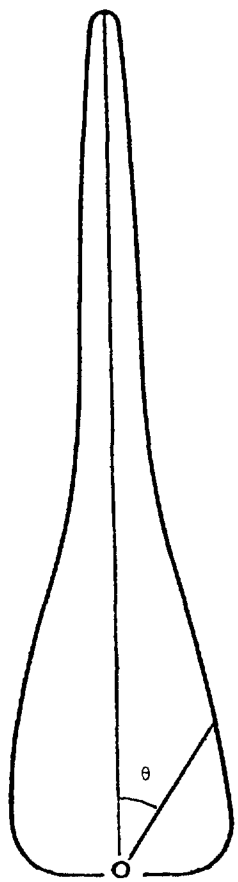

Figure 1. An example of a visual detection lobe.

start and end times of the ith encounter. Here, by definition, t_i is the time of detection, if a detection occurs; or the time of the end of the pass, if no detection occurs. Further, let $R_i(u)$ denote the range between the searcher and the target at time u during the ith encounter.

The probability, $P_i(k)$, of realizing the ith encounter is given by

$$P_i(k) = \begin{cases} k\theta_0(R_i(t_i))\exp\left\{-k\int_{s_i}^{t_i} \theta_0(R_i(u))\,du\right\} & \text{if detection occurs} \\ \exp\left\{-k\int_{s_i}^{t_i} \theta_0(R_i(u))\,du\right\} & \text{if no detection occurs.} \end{cases}$$

Now reorder the N pieces of data so that the first M are those cases for which detection occurs. Then the probability, $P(k)$, of having collected this batch of data is

$$P(k) = \prod_{i=1}^{N} P_i(k)$$
$$= k^M \prod_{i=1}^{M} \theta_0(R_i(t_i))\exp\left\{-k\sum_{i=1}^{N}\int_{s_i}^{t_i} \theta_0(R_i(u))\,du\right\}.$$

Differentiating this equation with respect to k and setting the result equal to zero yields the maximum likelihood estimator $\hat{k}$.

$$\hat{k} = M \Bigg/ \sum_{i=1}^{N}\int_{s_i}^{t_i} \theta_0(R_i(u))\,du. \quad (8)$$

The form of (8) is particularly appealing because $\hat{k}$ is directly proportional to the number of detections and inversely proportional to the total cumulative search effort applied against all targets. Moreover, $\hat{k}$ depends on the unsuccessful encounters only through the denominator of (8); those failures for which there was little chance of detecting the target do not have a large impact on $\hat{k}$. Note also that the computation of $\hat{k}$ involves no choice of a bin size and does not require straight or complete tracks. Once $\hat{k}$ has been computed, the model in (7) can be used to evaluate probabilities of detection for situations involving searcher speeds, meteorological visibilities, intrinsic contrasts, or visual angles for which no data are available.

The detection lobe model was developed by E. S. Lamar for the Operations Evaluation Group of the Office of the Chief of Naval Operations. A more complete description can be found in Koopman (1946) and in Lamar (1959). The maximum likelihood estimator for k is due to the authors. Weisinger describes a second physical model for visual detection that we also studied. This second model is based on an empirical formula in Koopman (1986). The detection lobe model provided a better fit to the Coast Guard data and so this second model was not pursued.

The Touchstone Model

Our touchstone model is based on the assumption that the lateral range function of a surface searcher is nonincreasing and the lateral range function of an air searcher is unimodal. (This unimodal assumption allows for the possibility of a blind spot underneath an air searcher.) Thus, this approach amounts to finding the nonincreasing function or the unimodal function that best fits the observed data.

More precisely, suppose that the data have been sorted into narrow lateral range bins (say, every 0.1 nautical mile). Further, suppose that there are n bins which have been numbered from 1 to n so that smaller numbers correspond to smaller lateral ranges. Let $w(i)$ denote the number of encounters in the ith bin and let $p(i)$ denote the proportion of the encounters in the ith bin that are detections.

Now, the best nonincreasing or unimodal fit to the observed data can be defined as follows. Let S_1 denote the set of nonincreasing functions on the integers 1 through n; let S_2 denote the set of unimodal functions on the integers 1 through n. For any function f defined on the integers 1 through n, let $T(f)$ be given by

$$T(f) = \sum_{i=1}^{n} (f(i) - p(i))^2 w(i).$$

So, $T(f)$ is the weighted squared difference between f and the function p defined above. The function f is a best nonincreasing fit to p if f is in S_1 and $T(f) \leq T(h)$ for all functions h in S_1. Similarly, the function f is a best unimodal approximation to p if f is in S_2 and $T(f) \leq T(h)$ for all functions h in S_2.

The Pool Adjacent Violators (PAV) algorithm finds the best nonincreasing fit to p (see Barlow, Bartholomew, Bremner, and Brunk 1972). Thus, this algorithm solves the problem of constructing the lateral range function for surface searchers in the touchstone model. Briefly, the PAV algorithm proceeds as follows. Starting with the first bin, the algorithm steps through the bins until it finds an index i such that $p(i) > p(i-1)$. (If no such index exists, p is already nonincreasing.) Having found such an index, it pools the $(i-1)$st and the ith bins, renumbers the resulting $n-1$ bins, and recomputes p. It repeats this process until the recomputed function is nonincreasing. This final version of p is the best nonincreasing fit to the original function p. A straightforward modification of this algorithm can be used to find the best unimodal fit to the function p. Hence, the algorithm also solves the problem of constructing the lateral range function for air searchers in this model.

As with the construction of empirical lateral range functions, the use of our touchstone model places restrictions on the data and has no underlying physical model. However, it does minimize the dependence on the choice of a bin size, at the cost of fairly weak assumptions on the form of the lateral range function. Thus, although this model does not provide an ideal solution to our estimation problem, it does offer a useful baseline for judging the results of the detection lobe model.

3. Application

This section describes the results that we obtained when the detection lobe model was applied to the Coast Guard visual detection data. This discussion is divided into three parts. First, the data are described and divided into a collection of homogeneous subsets. Second, the model parameter k is estimated for each subset. Subsets of data that yield statistically indistinguishable estimates of k are pooled. The result is a reduced data structure and the corresponding estimates of k. Finally, some remarks are included on areas for further research.

The Coast Guard Data

Between 1978 and 1981, the Coast Guard Research and Development Center conducted a series of visual detection experiments off the coast of Long Island. The data collected provides descriptions of more than 4,500 searcher/target encounters. Here each encounter consists of a searcher making a single pass by a moored target. The description of an encounter includes the type of searcher, the type of target, the searcher's track and speed, the searcher's time on task (used as a measure of fatigue), the prevailing environmental conditions (such as visibility, wind speed, and cloud cover), and, if a visual detection occurs, the position of the searcher at the time of detection.

In particular, the data required to apply the detection lobe model are available—with one exception. It is difficult in practice to measure the intrinsic contrast of the target. Since these measurements are not available in the Coast Guard visual detection data, default values for intrinsic contrast are assigned for the analysis that follows. After a review of the data and discussions with Coast Guard personnel it was decided that values of Co = 20 for persons in the water and Co = 40 for boats and rafts would be used.

The visual detection data compiled by the Coast Guard includes a variety of search scenarios. As a result, we felt that it was unlikely that a single value of the parameter k could adequately reflect all the data. Thus, the Coast Guard data were divided into a collection of homogeneous subsets. These subsets were determined as follows. Pei and Clark (1980) perform a principal component analysis of a large subset of the Coast Guard data. This analysis identified those search parameters that account for the most variation in the data. Five of these search parameters are not built into the detection lobe model: searcher type, target type, wind speed, cloud cover, and time on task. This suggested that a subdivision of the data should be based on the following four factors:

- Searcher Type. Four searcher types are used—cutter, patrol boat, helicopter, and fixed wing aircraft.
- Target Type. There are three target types—boat, raft, and person in the water.

- Weather. Two types of weather are used—fair and poor. Fair weather is defined to mean at most 12 knots of wind and at most 50% cloud cover. Poor weather is any weather which is not fair.
- Time on Task. There are two categories—low and high. For surface searchers the cutoff is 2 hours; for aircraft the cutoff is 1 hour.

Taken together, these factors divide the Coast Guard into $48 = 4 \times 3 \times 2 \times 2$ subsets. Since there are approximately 4,500 encounters in the Coast Guard data, the average subset contains about 94 encounters. Additional information on the Coast Guard visual detection data can be found in Edwards et al.

Applying the Methodology

The detection lobe methodology was applied to the 48 Coast Guard data sets and the model parameter k was estimated for each set. When a pair of subsets yielded similar values of k, a statistical test was performed to determine whether the two subsets could be pooled. The result of this pooling scheme was a reduced data structure. The 32 sets of this reduced data structure are listed in Tables I and II.

The model parameter k was estimated for each set in the reduced data structure. These estimates are given in Tables III and IV. In order to provide a broader context for viewing these results, Tables III and IV also list the sweep widths that correspond to the estimates of k, the sweep widths that were computed for these pooled sets using the touchstone model, and the sweep widths that were recommended in early versions of the Coast Guard's SAR tables. (These SAR tables are not based on the 1978–1981 data.) The sweep widths corresponding to the estimates of k were computed using Equations 1 and 7. More specifically, given k and the average values of the search parameters in each data set, (7) provides a means for computing the probability of detection along any path. In particular, (7) can be used to compute values of the lateral range function. These values of the lateral range function can then be used to estimate the integral in Equation 1, and hence, the sweep width.

A comparison between the values from the SAR tables and those generated by the two models shows that the SAR tables suggest lower sweep widths for rafts and persons in the water and higher sweep widths for boats. The lower sweep widths are not surprising because the methodology used in constructing the SAR tables is quite conservative. The higher sweep widths for boats may reflect the fact that the SAR tables group together all boats with lengths less than 30 feet. In the 1978–1981 data, all boats are 16 feet long. Thus, the two "boat" categories may not be comparable.

Our results can also be compared with the work of the Navy's ASWORG during World War II. In fact, Koopman (1946) uses the detection lobe model to analyze sightings of the wakes of submarines and surface ships by aircraft. This analysis yields a value for k of 6.3, which is larger than our estimates in Table IV. However, the wake of a ship, which sends back practically all of the light falling on it, is an excellent diffuse reflector. Thus, these results seem consistent.

Table I
Subsets in Reduced Data Structure: Surface Searchers

Subset	Weather	Searcher	Time on Task	Target	No. of Encounters
1	Fair	Cutter	Low	Raft	126
2	Fair	Cutter	Low	Person in water	60
3	Fair	Cutter	High	Raft	85
4	Fair	Cutter	High	Person in water	146
5	Fair	Cutter	All	Boat	194
6	Fair	Patrol boat	Low	Boat or raft	151
7	Fair	Patrol boat	High	Boat or raft	79
8	Fair	Patrol boat	High	Person in water	94
9	All	Patrol boat	Low	Person in water	144
10	Poor	Cutter	All	Raft	177
11	Poor	Cutter	All	Person in water	311
12	Poor	Cutter	High	Boat	122
13	Poor	All	Low	Boat	186
14	Poor	Patrol boat	Low	Raft	30
15	Poor	Patrol boat	High	Boat or raft	111
16	Poor	Patrol boat	High	Person in water	98

Table II
Subsets in Reduced Data Structure: Air Searchers

Subset	Weather	Searcher	Time on Task	Target	No. of Encounters
1	Fair	HELO	Low	Boat	92
2	Fair	HELO	Low	Raft	78
3	Fair	HELO	High	Boat or raft	160
4	Fair	Fixed wing	Low	Person in water	85
5	Fair	Fixed wing	All	Boat or raft	234
6	Fair	Fixed wing	High	Person in water	146
7	All	HELO	Low	Person in water	168
8	All	HELO	High	Person in water	246
9	Poor	HELO	Low	Boat	76
10	Poor	HELO	Low	Raft	47
11	Poor	HELO	High	Boat	150
12	Poor	HELO	High	Raft	91
13	Poor	Fixed wing	Low	Boat	80
14	Poor	Fixed wing	Low	Raft	98
15	Poor	Fixed wing	High	Boat or raft	234
16	Poor	Fixed wing	All	Person in water	421

Table III
Estimates of k and Sweep Width: Surface Searchers

Subset	k	Sweep Widths		
		Detection Lobe	Touchstone	SAR Tables
1	2.75	5.0	5.5	1.8–1.9
2	3.02	0.9	0.8	0.2
3	1.09	4.0	3.9	1.8–1.9
4	1.55	0.6	0.6	0.2
5	0.65	3.6	4.1	3.9–5.2
6	0.68	3.2	3.4	1.8–5.2
7	0.33	2.7	2.4	1.8–5.2
8	0.60	0.3	0.3	0.2
9	0.85	0.4	0.5	0.2
10	1.49	4.2	4.0	1.8–1.9
11	0.99	0.5	0.5	0.2
12	0.23	2.2	2.5	3.9–5.2
13	0.34	2.7	3.1	3.9–5.2
14	1.28	4.0	3.3	1.8–1.9
15	0.50	2.8	2.9	1.8–5.2
16	0.30	0.2	0.2	0.2

Note: Values of k are given in inverse hours. The estimates of sweep widths obtained from the detection lobe model are based on the average values of the search parameters in each data set. Since the SAR tables are organized differently, only representative ranges of values are given in some cases.

The pooling test discussed above is based on the techniques in Chapter 33 of Cramer (1946). A further description of this test and the entire data analysis may be found in Weisinger. In particular, this report includes plots of the lateral range functions corresponding to all 32 sets in the reduced data structure. The SAR tables can be found in U.S. Coast Guard (1973).

A Final Perspective

A computer program that combines the detection lobe model with our analysis has been delivered to the Coast Guard. This program is used to provide visual detection performance predictions for search planning. More specifically, when a search problem arises in which the searcher type, target type, time on task, wind speed, and cloud cover match one of the 32 situations in the reduced data structure, the program combines the corresponding value of k with the meteorological visibility, the target area, the intrinsic contrast, the searcher altitude, and the searcher speed, and generates a lateral range function and a sweep width. While this program represents an important search planning tool for the Coast Guard, it by no means completes the study of visual detection performance that was begun by the ASWORG during World War II. In fact, to illustrate this point, we conclude our discussion by citing two areas that require additional research.

First, a weakness of the detection lobe model is its inability to model the long tails observed in some of the lateral range functions generated by our touchstone model. One reflection of this difficulty can be seen in the estimates of sweep width provided by the detection lobe model and the touchstone model. In 27 out of the 32 sets in the reduced data structure, the estimate given by the touchstone model lies inside the 95% confidence interval of the detection lobe model

Table IV
Estimates of k and Sweep Width: Air Searchers

Subset	k	Sweep Widths: Detection Lobe	Sweep Widths: Touchstone	SAR Tables
1	4.89	4.1	4.7	4.0–5.3
2	2.57	2.9	2.6	1.8–1.9
3	2.72	3.4	3.5	1.8–5.3
4	5.78	0.3	0.3	0.2–0.3
5	4.42	3.3	3.8	2.1–5.5
6	2.50	0.2	0.1	0.2–0.3
7	2.94	0.3	0.3	0.2
8	1.40	0.2	0.2	0.2
9	2.39	3.3	3.8	4.0–5.3
10	1.27	2.0	2.0	1.8–1.9
11	1.43	2.6	3.1	4.0–5.3
12	2.27	2.6	2.3	1.8–1.9
13	3.55	2.5	2.5	4.2–5.5
14	2.18	1.9	1.9	2.1–2.6
15	1.91	1.9	1.6	2.1–5.5
16	2.36	0.2	0.2	0.2–.03

Note: Values of k are given in inverse hours. The estimates of sweep widths obtained from the detection lobe model are based on the average values of the search parameters in each data set. Since the SAR tables are organized differently, only representative ranges of values are given in some cases.

estimate. In each of the remaining 5 cases, the touchstone model estimate lies above the confidence interval, and an examination of the lateral range functions shows that the touchstone model includes a long tail while the detection lobe model does not.

Second, the lateral range functions estimated for many of the air searcher cases by the touchstone model have a definite unimodal shape (that is, these functions increase and then decrease). This result confirms a similar observation by Pei and Clark. It is not clear why this unimodal behavior exists. However, the detection lobe model certainly cannot account for this shape.

Improvements to the detection lobe model in either of these areas would extend the model's utility in planning search operations and in saving lives—which really is the bottom line for this work.

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