A Truncated Sweep Width Exercise: Obtaining Search Planning Data More Quickly and Comparing Sweep Width Values in Subjectively Similar Environments in Ohio and Pennsylvania

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Abstract

While the effective sweep width (*W*) method appears to provide accurate, objective probability of detection (POD) for search planning, the need for an extensive library of locally relevant *W* values poses an obstacle to adoption. To investigate means for shortening such data acquisition, we conducted a roughly third-scale sweep width exercise in Bellview, Ohio, U.S.A., leveraging a more data-efficient means of deriving POD-validated *W*s previously described. We compared the results to previous *W*s obtained in a subjectively similar area in Wexford, Pennsylvania, finding that the sparsity of data in the smaller course sometimes results in poor fits. However, when good POD-curve fits can be derived, the *W* values for the similar areas appear to be statistically indistinguishable.

KEYWORDS: SAR, effective sweep width, probability of detection, search theory

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Introduction

The SAR community has made great strides in using lost-person behavior to prioritize which areas to search initially (Koester 2008). But our state-of-the-art lags in re-assessing search efforts in the minority of search incidents in which those initial high-priority areas have been searched without finding the search subject. In theory, the equation

1. POS = POD X POA

tells us that, to maximize our probability of success (POS, finding the subject), we should shift our efforts to new areas as the probability of area (POA, the probability that the subject is in a given area) of searched areas is knocked down by the probability of detection (POD, the probability that search efforts in that area would have found the subject if present there) of the search efforts we've already made (Charnes and Cooper 1958).

One problem with this approach is that asking search team leaders to estimate POD, the traditional means of acquiring that number, produces large errors, averaging about 25% and often larger than that (Koester et al. 2004). The effective sweep width method, pioneered by the military, promises to provide us with more accurate PODs (Koopman 1980, Koester et al. 2004). It provides us with a distance-scaled number, *W*, that describes how a detector (whether a human searcher, a dog team, a drone, or so forth) effectively sweeps a corridor as it moves through an area, detecting as many search objects outside of that corridor as it misses inside (Fig. 1, from Cooper DC et al. 2003).

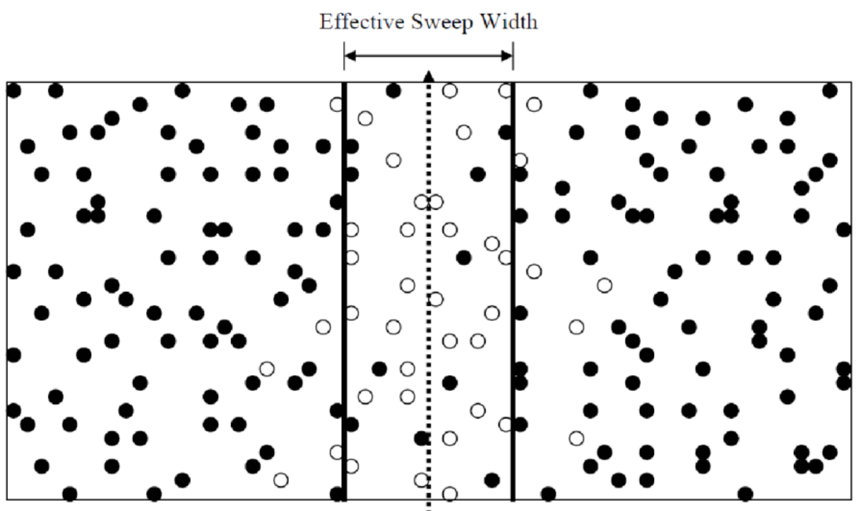


Figure 1: Illustration of a detector "sweeping a path" through a search area. Effective sweep width, or W, is the combined lateral distance to left and right of the detector's path at which misses (black circles) inside the envelope equal detections (open circles) outside.

Two obstacles arise in expanding the worldwide library of *W* values. The first is that it is not clear how sensitive *W* is to minor environmental differences. Broadly differing ecoregions certainly produce different *W* values for the same search object (Koester et al. 2004); so do seasonal differences in the same location (Chiacchia and Houlahan, 2010). But it is not clear if locales that *look* the same to a SAR-experienced observer have similar *W*s. Obviously, if this were true it would enable wider use of a more limited library.

Another obstacle is that sweep width exercises to determine local *W*s are staffing- and time-intensive to carry out. Using three to six workers and 18 to 25 searchers, we are able to set up, conduct, and tear down a sweep width course in four to five days. If it were possible to shorten that time, possibly by shortening the roughly 3,000-meter course length required for our previous sweep width exercises, it would also enable the *W* library to grow more quickly.

Koester et al. 2004 found that 100-200 detection opportunities (DOs, either detections or misses on a given search object) were necessary to obtain a stable *W* value. Recently, one of us reported a new means of deriving *W* that makes more efficient use of detection data, encouraging us to attempt a sweep width exercise at the lower end of this range (Chiacchia and Houlahan, 2023).

On June 11, 2022, we ran a roughly third-scale sweep-width exercise at Hidden Hollow Campground in Bellville, Ohio, to determine the *W* values there. The following report describes the results of that exercise, as well as comparisons with previous data from the subjectively similar State Game Lands 203 in Wexford, Pennsylvania (Chiacchia and Houlahan, 2010 and 2023).

Methods

We conducted the human visual sweep width experiments in the manner of Koester et al. 2004, with modifications previously described (Chiacchia and Houlahan 2010), using the IDEA Microsoft Excel worksheet provided by R. Koester and N. Guerra to automatically generate a randomized plan for a sweep- width course. We calibrated the courses with average maximum detection range (AMDR) values obtained in our earlier sweep width exercises in Wexford, Pa. (Chiacchia and Houlahan, 2010 and 2023). Note that we were able to do this partly because the POD-based derivation of *W* does not require a crossover point and thus is tolerant to inaccurate calibration (Koester et al. 2004, Chiacchia and Houlahan, 2023).

We placed the following search objects in the positions generated by the IDEA worksheet, using the methods of Koester et al. 2004:

- Seven high-visibility adult mannequins: white Tyvek suits, stuffed with packing boxes to give them roughly the same cross-section as a prone human, wearing blaze orange safety vests. Note that three placements generated by the worksheet were not visible from the course due to vegetation or terrain, enabling us to place these mannequins at shorter distances, counting the original random placements as zero-detection “virtual placements” (Koester et al. 2004), for a total of 10 placements for these search objects.
- Seven low-visibility adult mannequins: the same Tyvek suits, spray-painted olive drab.
- Seven high-visibility clues: bright yellow work gloves obtained in bulk from Tractor Supply, Brentwood, TN, USA.

- Seven low-visibility clues: dark brown work gloves from Tractor Supply.

The resulting course was 1,050 m long, beginning at USNG coordinates 17T LE 78496 99590 and ending at 17T LE 78091 99220 (See Fig. 2). The first search object, a high-vis mannequin, was randomized to a position 19 m down-trail from the beginning of the course (though note the actual placement, obtained through a GPS fix, was somewhat farther along the course); the last, a high-vis clue, at 1,024 m. Positions of the placements were corrected via GPS when the uncertainty in the GPS fix (approx. 3 m) was half of the lateral distance from the course or smaller, and the DOs were scored via the map rather than the linear detection scoring log of Koester et al. 2004.

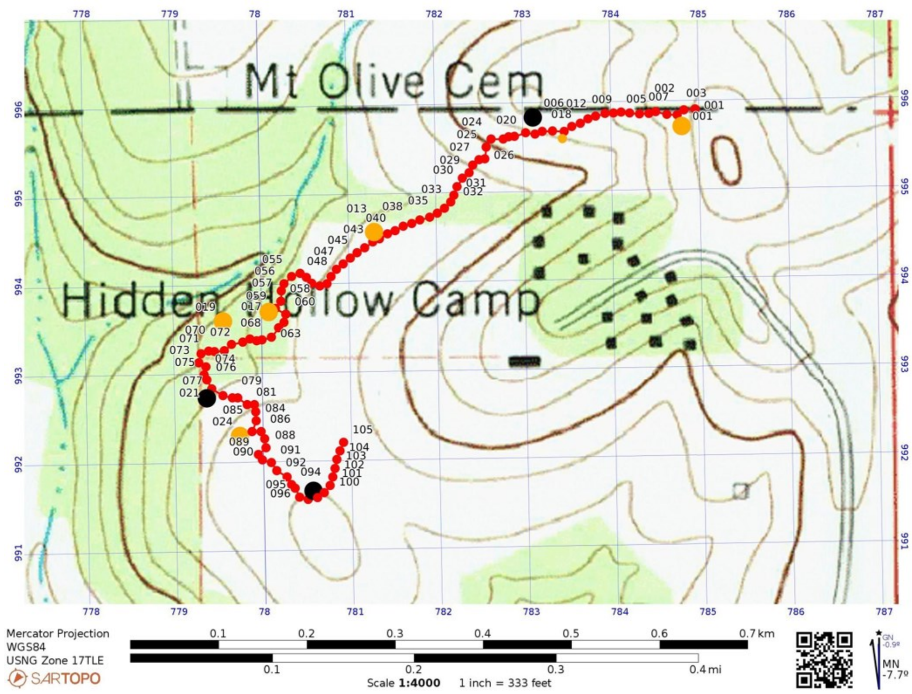


Figure 2: Hidden Hollow Camp sweep width exercise. Red dots show distance flags marking the course (distance down the course is 10X the number beside each flag position in meters); large orange dots are high-vis mannequins, small orange high-vis clues, and large black dots low-vis mannequins. Note that for clarity, search objects that were too close to the course to resolve on the map are not shown. Image generated with SARTopo (CalTopo LLC, Truckee CA, USA).

Fourteen members of the Ohio Special Response Team walked the course, accompanied by data loggers who helped them stay on the flagged course and recorded sightings or suspected sightings of clues (note false sightings were also recorded but by design did not affect the results). Of these, 13 produced usable logs, with one incomplete form that was difficult to score and so was disregarded. This produced 130 DOs for the high-vis mannequins and 91 each for the other search objects.

In keeping with our plans, the course took one day for the two authors to set up, half a day to conduct, and half a day to tear down, albeit the latter with help from the participants and Hidden Hollow Camp staff.

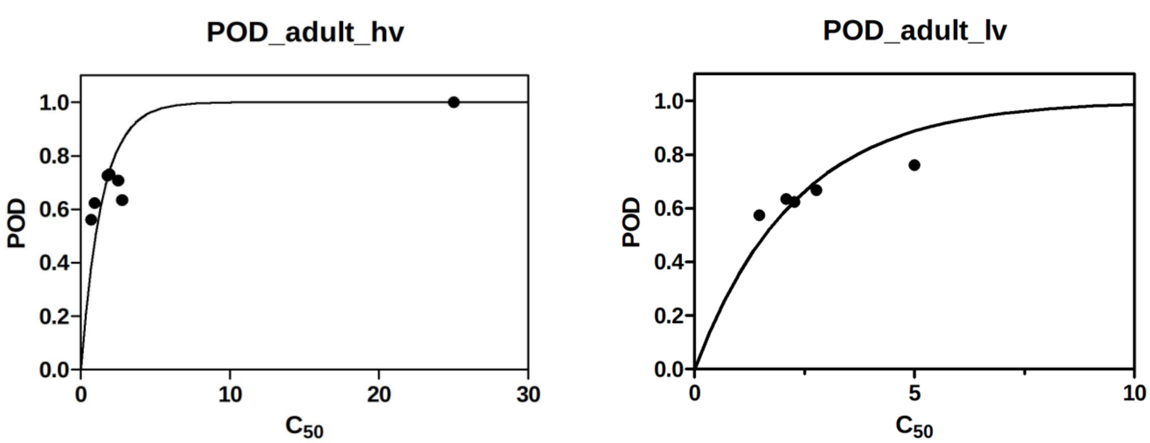
For each search object and as previously described (Chiacchia and Houlahan, 2023), we generated a curve that related PODs observed, cumulated from the marked course each searcher followed outward to C_{50} (coverage, where C = *W*/L, *W* = an arbitrary sweep-width value of 50 m, and L = lateral distance from the detector's path). By plotting the PODs against C_{50}, we obtained the true value of W from a least-square fit to POD versus C_{50} using the "random search model" equation:

2. $\text{POD} = 1 - e^{-(C_{50} W/50\text{m})}$

Mapping was accomplished using a Garmin GPSMap 62sc GPS receiver (Garmin International, Olathe, KS, USA) and the SARTopo online mapping software (CalTopo LLC, Truckee CA, USA). For the least-square fit and subsequent analyses, we employed GraphPad Prism version 5.00 for Windows (GraphPad Software, San Diego, CA, USA, www.graphpad.com) to perform statistical testing. Data are expressed as mean±standard deviation (SD). All tests were two-tailed, with P<0.05 set as the threshold for statistical significance.

Results

For each search object, we generated a curve that related POD as measured in the field to C_{50} (Fig. 3).



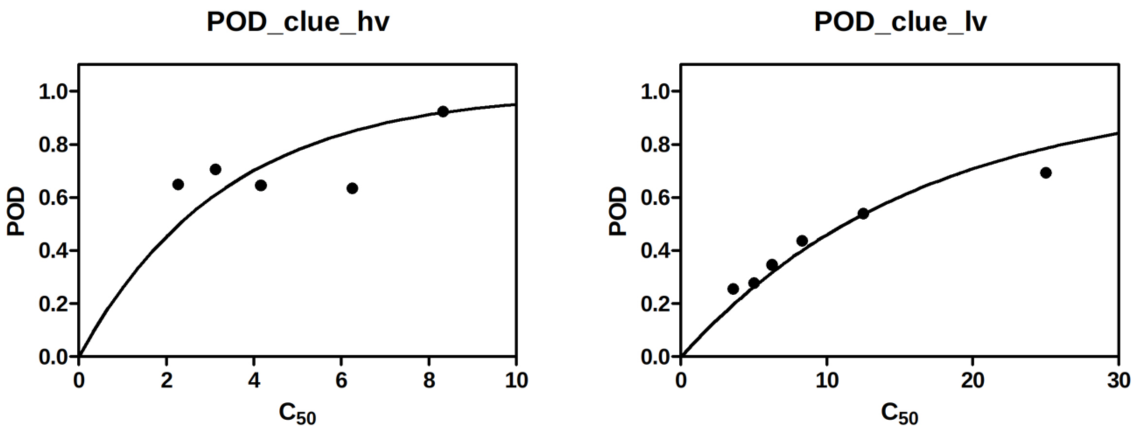


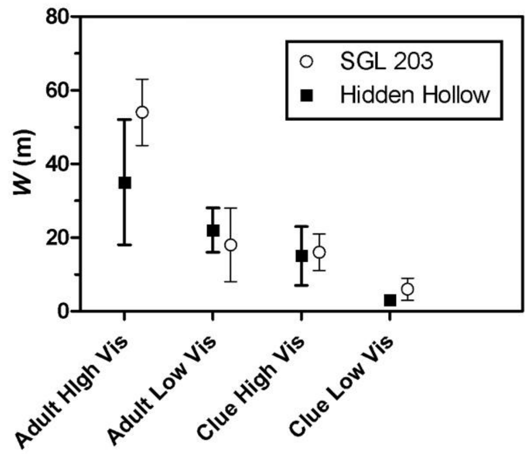
Figure 3: POD curves for each of the search objects. Note that some of the curves have fewer points than the total number of placements for each (10 for the high-vis mannequin, seven for the others) because of identical lateral distances for some of the placements.

The resulting *W* values of the least-square fit to equation 2 were:

Search object	*W* (meters)	R-square
High-vis adult	35±15	0.053
Low-vis adult	22±6	0.569
High-vis clue	15±7	-0.400
Low-vis clue	3±1	0.899

In setting up the exercise, it struck us that the terrain and vegetation were more than reminiscent of those at the Wexford, Pennsylvania, site. To investigate this subjective impression further, we conducted a two-way ANOVA of the Ohio data versus the earlier Pennsylvania summer data reported previously (Fig. 4, Chiacchia and Houlahan, 2010 and 2023).

Figure 4: ANOVA comparison of Ohio (Hidden Hollow) and previous Pennsylvania (State Game Lands 203) W



*values. ***=P<0.001; other comparisons no significant difference.*

The two-way ANOVA generated P<0.0001 for the row factor (corresponding to search objects), and P=0.027 for the column factor (locations). There was interaction between the two, with P=0.0015. A Bonferroni post-test comparing the results at Hidden Hollow and State Game Lands 203 for each search object showed P<0.001 for the adult high visibility mannequin, and P>0.05 for the other search objects. (The high-vis mannequin having a different *W* in the two locations, while the others did not, is the likely cause for the significant interaction P-value.)

Discussion

The shortened sweep width course produced what we believe to be usable numbers, though the high-vis search object data had an objectively poor fit to the curves. This is a risk in collecting relatively small data that should be kept in mind; our attempt to produce strong *W* values with a smaller course was a mixed bag in that regard.

Interestingly, except for those for the high-vis mannequin, none of the numbers from Hidden Hollow were significantly different from what we saw at State Game Lands 203. Our suspicion is that *W* values for the two sites — and, probably, the two regions — are essentially identical; certainly, the relatively good fits and lack of significant difference for the low-vis mannequin and clue would support this interpretation. Given the poor fits for the high-visibility search objects, neither the significant difference seen with the mannequin nor the non-significant difference seen with the clue can be interpreted in a straightforward manner.

Consider, in addition, the fact that the POD curve method often detects significant differences between *W* values that in turn result in minimal changes in PODs (Chiacchia and Houlahan 2023). In Fig. 5 we see the Ohio data for the high-vis mannequin, plotted with both the fit curve (solid line) and the curve that would have resulted with an identical *W* to the Pennsylvania data. Indeed, the POD differences are minimal, at most on the order of 10-15%. At the critical 50% POD point, where search efforts are likely to shift the POA for a given area in favor of other areas (Charnes and Cooper 1958), that difference is ~10%. Again, we favor the interpretation that the *W* values for the two sites are not different enough to be operationally significant.

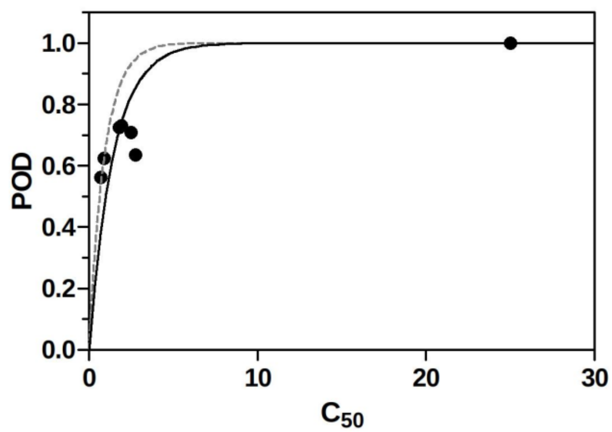


Figure 5: Comparison of Ohio (black solid line) and Pennsylvania (gray dashed line) random-search-model curves for the high-vis mannequins plotted against the Ohio data.

Limitations of the Current Study

The Pennsylvania full-vegetation data were acquired in the late summer, while the Ohio numbers were from the late spring. While there's a possibility of a seasonal difference here, we expect it will be minimal, as the woods in Hidden Hollow were clearly fully leafed out and thus similar to the summer conditions in Pa.

Another caveat to bear in mind is that we didn't collect enough data to separate the search objects placed in open (open field, woods with light undergrowth) versus thick (heavy-undergrowth woods, brush) vegetation. While the placement of the search objects along the course was random, the course itself was not, and so the *W* figures will depend on whether the mix of open and dense in the course is representative of the area.

It has been our experience that searchers have a kind of epiphany when they see their first mannequin. It isn't clear whether obtaining a search image in this way improves on their sweep width before that first detection, but as the randomization typically places at least one mannequin fairly early in the course, it should have a minimal effect. Nonetheless, the possibility exists that searchers improve while walking the first fraction of the course, and so a shorter course may be more affected by any such phenomenon than a longer one.

Conclusions

While the effective sweep width (*W*) method appears to provide accurate, objective probability of detection (POD) for search planning, the need for an extensive library of locally relevant *W* values poses an obstacle to adoption. To investigate means for shortening such data acquisition, we conducted a roughly third-scale sweep width exercise in Bellview, Ohio, USA, leveraging a more data-efficient means of deriving POD-validated *W*s previously described. We compared the results to previous *W*s obtained in a subjectively similar area in Wexford, Pennsylvania, finding that the sparsity of data in the smaller course sometimes results in poor fits. However, when good POD-curve fits can be derived, the *W* values for the similar areas appear to be statistically indistinguishable.

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Donald A. Scelza, EMT-P, is the task force leader and a medical specialist & rescue specialist in the Pennsylvania Strike Team 1 US&R team. A Fellow of the Appalachian Search and Rescue Conference, he is a search manager for Allegheny Mountain Rescue Group of Pittsburgh, Pa., and MARG. His business management experience includes management of small and large teams in the development of new products using advanced technologies. He has previously been chair of the Appalachian Search and Rescue Conference and president of Cranberry Township Emergency Medical Service, Pennsylvania.

Abbreviations

AMDR: Average maximum detection radius, the mean distance at which an observer cued to the location of an object can see it.

C: Coverage, the ratio of effective sweep width times the path length of a detector within an area to its size.

C_{50}: Coverage assuming an effective sweep width of 50m.

DO: Detection opportunity, a detection or miss of a search object at a right angle (lateral) to the detector's path.

POA: Probability of area, the estimated probability that a search object is contained within a given area.

POD: Probability of detection, the probability that a given detector will detect a given search object within an area under certain environmental conditions, assuming that object is in the area.

POS: Probability of success, the probability that a given search effort will detect a search object within a given area being searched (a "segment"). Equal to POA X POD.

W: Effective sweep width, a distance-denominated term defining the envelope within which a given detector's number of misses on a search object equals the number of detections outside, under specific environmental conditions.

References

Charnes A, Cooper WW. (1958) The theory of search: optimum distribution of search effort. Management Sci. 1958;5:44-50.

Chiacchia KB, Houlahan HE. (2010) Effectors of Visual Search Efficacy on the Allegheny Plateau. Wilderness Environ Med. 2010;21(4):188-201.

Chiacchia KB, Houlahan HE. Deriving (2023) Objective Probability of Detection for Missing-Person Search: Validating Use of Effective Sweep Width and Associated Mathematical Models. Journal of SAR. 2023;1(1):1-36.

Cooper DC, Frost JR, Robe RQ. (2003) Compatibility of Land SAR Procedures with Search Theory. Alexandria, VA: Potomac Management Group Inc;

Koester RJ, Cooper DC, Frost JR, Robe RQ. (2004) Sweep Width Estimation for Ground Search and Rescue. Alexandria, VA: Potomac Management Group Inc;

Koester RJ. (2008} Lost Person Behavior. Charlottesville, VA: dbS Productions

Koopman BO. (1980) Search and Screening: General Principles with Historical Applications. Elmsford, NY: Pergamon Press;