Head, Belt, Boots: Obtaining Consistent Probability of Detection in Human Visual Search

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Abstract

A key lost-person search method is the “grid team,” a line of searchers moving abreast through the woods. The optimum spacing for such searchers is not clear, however. We have determined the spacing necessary for searchers to see their immediate neighbors’ head, belt, or boots at sites in West Virginia in the summer and in Pennsylvania in the summer and winter. An analysis of the probabilities of detection (PODs) expected from previously or newly measured effective sweep width (*W*) values in those locations for each of these spacings suggests that each offers a consistent and useful POD for a given search object that does not appear to be affected by location or season by an operationally significant amount.

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

Literature Review

In lost person search, limited staffing makes balancing speed with thoroughness an imperative. Despite profound advances in our ability to predict the behavior of missing people in the woods (Koester RJ, 2008), we still must prioritize search efforts geographically via the educated guess of extrapolating from past search subjects' behavior. If we knew a given area contained a missing person, then no probability of detection (POD), no thoroughness of effort, would be wasted. But searching a given area with the metaphorical fine-toothed comb does a search subject no good if they aren't there.

Using the Bayesian equation:

1. POS = POA X POD

we achieve success (probability of success, POS) by maximizing our ability to search the correct area (probability of area, POA) as well as our ability to detect the subject (POD) (Koopman BO, 1980). These factors mean that, when we search a segment (an area searchable by a single modality within a 6-hour operational period or less) we must achieve a high enough POD so that its POA after we are done has been lowered significantly. Significance in this case meaning that another segment in our larger search area now has a higher POA and priority. But this must be done without searching so slowly that we linger too long in an empty area.

A workhorse search technique in ground search and rescue is the "open grid team," sometimes called a sweep search team. In this method, a group of (very) roughly 6 searchers array themselves in a line abreast, with a fairly large distance between each. They then move forward, maintaining that spacing as they search. Often the team will need to pivot and repeat several times to cover an assigned search segment (NASAR, 2018).

While open-grid search has proved successful in many deployments around the world, optimal spacing between the individual searchers is tricky to derive. A longer distance spreads the team out and enables them to search areas more quickly; a shorter distance produces a higher POD at the cost of taking longer to cover a given segment. How to balance these is a microcosm of the need to balance speed and thoroughness in a larger sense.

Search managers and field team leaders have used several methods for spacing searchers in a grid team to try to achieve a predictable POD prospectively. In recent years the effective sweep width method has grown to become the gold standard for calculating POD, with multiple reports demonstrating how it produces accurate PODs in field conditions (Koester RJ et al. 2004, Koester RJ 2020, Chiacchia et al. 2023). It relates effective sweep width, or *W*, a distance-labeled parameter, to POD via a mathematical model (Koopman BO, 1980).

While more than one mathematical model has been used to convert spacing via effective sweep width to POD, arguably the most common is the "random search" model, a conservative (i.e., tending to underestimate POD in the absence of corrected *W* values — see Chiacchia et al. 2023) model based on the idea that a searching modality will move through the terrain with a random navigational error:

2. $POD = 1 – e^{-C}$

Where C, or coverage, is:

3. $C = nW/A$

Where n is the number of detectors in a given search effort; *W* the effective sweep width for that type of detector, search object, and environmental conditions; and A is the size of the area being searched.

For a grid team, equation 3 can be simplified to:

4. $C = W/G$

Where G is the grid width — the distance between each pair of searchers in the team, given a single pass of the team through the search area. The issue, then, becomes one of selecting and maintaining a value for G that produces the desired C and POD.

One method for spacing teammates is to effectively ignore prospective POD and simply choose a spacing that minimally trained searchers can maintain. This method is to space searchers to keep each other "within sight." It is relatively easy to use but is not well defined, and so does not provide a consistent distance, let alone a predictable balance between speed and thoroughness. (We should note that in any case adjacent searchers remaining visible to each other is critical, as once one's neighbor moves out of visual range there is no way to determine how big the gap has become and significant command and control issues over the search team arise.)

Another method, called "critical separation," involves placing an object in the area to be searched (or a nearby area representative of it), with the searchers taking positions on opposite sides of the object, moving toward and away until they just lose/regain sight of it in a process sometimes referred to as a "Northumberland rain dance." They then look up to the searcher across from them; that distance is the critical separation to be used to space the team members (Perkins and Roberts 1989). While a practical method for spacing searchers at a useful distance, critical separation suffers from limitations as well. For one thing, the relationship between the object used for the separation exercise and the search object (which may be any number of clues generated by the lost person or the lost person themselves) means that the POD achieved with this method is typically not predictable (Chiacchia 2020). Perhaps more importantly, the method requires searchers to memorize the distance to the searcher opposite them and maintain that distance while moving through uneven terrain and vegetation, all the while searching visually. The difficulty of maintaining any arbitrary spacing can produce errors in POD of 25% or higher (Perkins 2018).

The effective sweep width method enables us to obtain objective probabilities of detection within a specific distance around the detector's path (Koopman 1980, Koester et al. 2004, Koester 2020, Chiacchia and Houlahan 2023). Arguably the most common method for achieving this, as taught in the Fundamentals of Search and Rescue course (NASAR 2018), is to space searchers based on measurement of detection radius (Rd) in a method similar to the rain dance above. Rd is the mean distance at which the desired search object can just be seen by searchers cued as to its location (Koester et al. 2004). As *W* has a roughly linear relationship with Rd (Koester et al. 2014), this method does not require advance knowledge of *W*, which unlike Rd requires many searchers and multiple days of setup, conducting, and tear-down to measure (Koester et al. 2004).

There are disadvantages to the Rd method, however. It relies on an estimated *W* value, whose accuracy depends on the color of the search object (Koester et al. 2014). Also, placing searchers at such an otherwise arbitrary distance again poses the issue of having to measure that distance, as well as to memorize and maintain it while searching. As with the rain dance, this can be difficult in practice (Perkins 2018).

When *W* values are known, effective sweep width may also be directly used to determine spacing. Given a desired POD and measured *W* values for a given search object and environment, we can use this method to calculate the spacing necessary to achieve that POD. While likely producing the most accurate PODs in theory, this method once again requires maintaining a memorized distance while searching, which undermines that accuracy.

Another method, "head, belt, boots," is worth considering. In this technique, each searcher spaces so that their neighboring searchers' heads are just visible through the vegetation and terrain, their belts are just visible, or their boots are just visible. The searchers then maintain spacing in a dynamic way, moving closer together or farther apart to keep the head, belt, or boots target just in sight. Note that heads, belts, boots differs from "keep in sight" described above because in each case searchers are using a specific target on the next searcher over rather than a vague directive of keeping that person more or less in sight, and so offers the possibility of far more consistent spacing.

While still requiring attention on spacing while searching, heads, belts, boots does not necessitate memorizing an arbitrary distance. The required spacing can be instantly recognized and adjusted. Moreover, as one end of an open grid line is typically anchored to a path — a trail or creek or ridge-top that defines the edge of the search segment, or a flag line laid down at the teams' previous pass through the area — typically the team can "dress left" or "dress right," with each member only maintaining spacing with the single teammate in the direction of that anchor line, effectively halving the attentional effort to maintain the line.

The head, belt, boots method offers another potential benefit, stemming from other search-relevant measurements. *W* values have a roughly linear relationship with Rd (Koester et al. 2004 and 2014) in a method similar to the Northumberland rain dance. This relationship, which relates the distance at which one can spot an object when its location is known (Rd) with the distance at which it is likely to be detected when a searcher does not know where to look for it (*W*), makes intuitive sense. But it was not predicted by search theory and needed to be demonstrated empirically (Koester et al. 2014).

Given that the distance for spotting a known object has a relatively simple relationship to its *W*, does it follow that the distance for seeing a neighboring searcher's head, belt, or boots is also proportional to *W*? And if so, does that mean that spacing searchers at head, belt, or boots distances produces a consistent POD across different environments? In this report, we measure head, belt, and boots distances for two locations — State Game Lands Number 203 in Wexford, Pennsylvania, USA, and Snake Hill Wildlife Management Area, Morgantown, West Virginia, USA — and, using *W* values previously measured for the former (Chiacchia and Houlahan 2010 and 2023) and newly measured for the latter, compare the predicted POD values for spacing searchers at either the head, belt, or boots distances for two search objects in summer and winter.

Methods

We conducted the human visual sweep width exercise in the Snake Hill Wildlife Management Area in the manner of Koester RJ 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 that followed extant trails. We calibrated the course with Rd values obtained at one random location, 17S PD 00646 85942 (US National Grid). Note we had randomized a second location for Rd determination as well, at 17S PD 00254 86576, but upon arriving at that location discovered it was a vertical drop that would not have been safe to perform the measurements in. Rather than move a randomized location, we elected to rely on the values obtained only at the former coordinates.

The course that we chose was above and intentionally avoided an elevation of roughly 550 to 600 m, where the rhododendron (aptly named *Rhododendron maximum*) grows as a solid mass and profoundly impedes both movement and visibility. While sweep width values for this environment would be interesting, the values would clearly be low enough, and movement through the environment difficult enough, to make grid search impractical. Moreover, a course that included both heavy rhododendron and more open woods would in effect be two sweep width courses, necessitating separate analysis of the two environments and splitting of data, leading to weaker statistical comparisons. Our course as laid out between an elevation of 600 and 650 m (See Fig. 1) therefore had a mix of open largely deciduous woods, woods with heavy undergrowth including greenbrier, and some patchy but not continuous rhododendron, and is more representative of areas in which we would task traditional grid searchers.

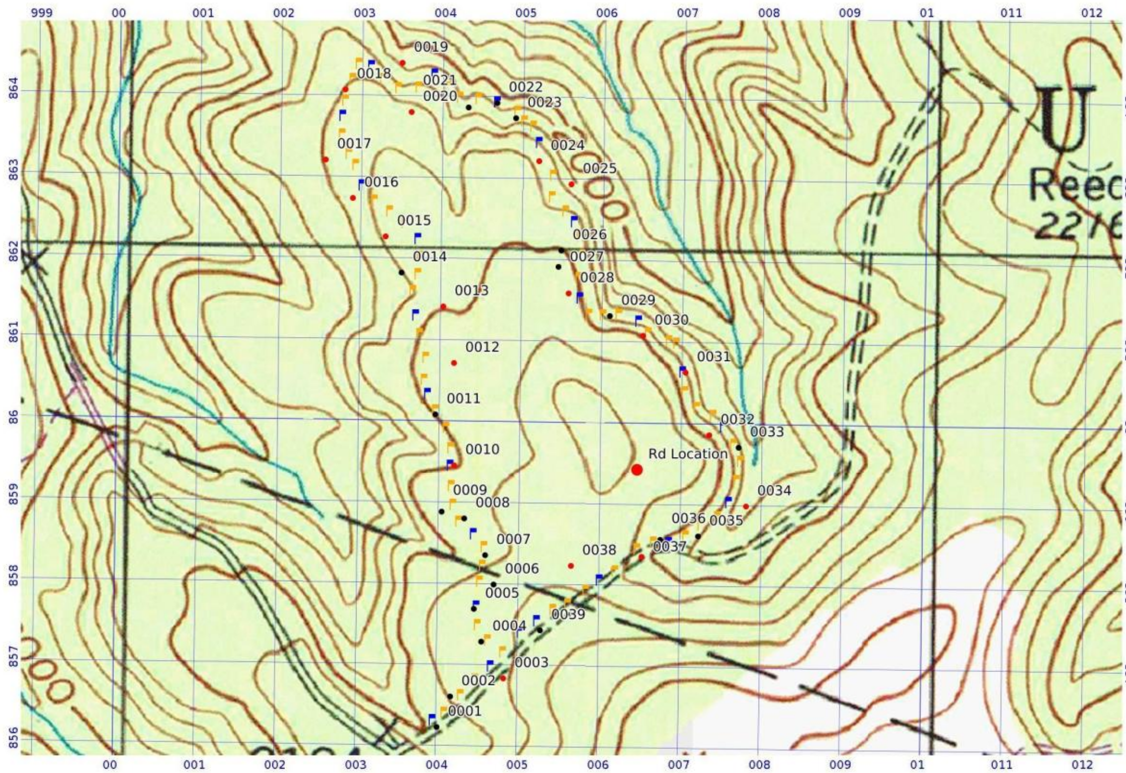
We placed the following search objects in the positions generated by the IDEA worksheet, using the methods of Koester et al. 2004:

- 19 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. One of these randomized placements lay at a lateral distance that was not visible from the course due to thick vegetation. We therefore counted the original placement as “virtual” (Koester et al. 2004), scoring it as an automatic miss for each searcher, and placed the physical mannequin at a shorter lateral distance just visible from the course. This resulted in a total of 20 detection opportunities (DOs) for these search objects.
- 20 low-visibility adult mannequins: the same Tyvek suits, spray-painted olive drab. Two of the randomized placements were not visible from the course and were treated as above, resulting in a total of 22 detection opportunities, with two of them automatic misses.

The resulting course was 2,225 m long, beginning at 17S PD 00392 85624 and ending at 17S PD 00500 85733 (See Fig. 1). The first search object, a low-vis mannequin, was randomized to a position 9 m down-trail from the beginning of the course; the last, a high-vis mannequin, at 2,208 m. Locations of course flags and mannequins were recorded with either an Alpha 200i or a GPSMAP 66st GPS receiver (Garmin International, Olathe, KS, USA).

Fourteen searchers blinded to mannequin placement walked the course beginning at 09:32 EDT on Sept. 14, 2024, and ending at 18:10 the same day. Data loggers helped them stay on the flagged course and recorded sightings or suspected sightings of clues (false sightings were also recorded but by design did not affect the results). This produced a total of 280 detection opportunities (DOs, hits or misses) for the high-vis mannequins and 308 for the low-vis.

Figure 1. Snake Hill WMA Sweep Width Course. Blue flags, unlabeled, represent start, finish, and 100 m marks along the course length; orange flags, 25 m marks. Low-vis mannequins, black dots, are labeled with their clue numbers, as are high-vis mannequins, red dots. These are the actual locations of the mannequins; virtual placements are not shown. Location for the Rd determination is marked with a large red dot. Note trails are not shown, for clarity. Image generated with SARTopo (CalTopo LLC, Truckee CA, USA).



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, with L = lateral distance from the detector's path). By plotting the PODs against C_{50}, the coverage assuming *W* = 50 m, we obtained the true value of *W* from a least-square fit to POD versus C_{50} using the "random search model" equation:

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

As part of the Snake Hill exercise and following up on the earlier exercises at SGL 203, we conducted a "heads, belts, boots" measurement at the same locations as used to measure Rd values to calibrate each course (Koester et al. 2004, Koester et al. 2014). Four searchers carried out these measurements, requiring two evolutions per location to carry out measurements from each of the eight semi-cardinal compass directions. These measurements were carried out on Sept. 3, 2023 (SGL 203 summer), Dec. 31, 2023 (SGL 203 winter), and Sept. 12, 2024 (Snake Hill summer).

To accomplish this, we adapted the Rd method of placing the desired search object (in this case, the low- and high-vis mannequins) on the randomized spot(s) in each search area. This process is similar to the "Northumberland rain dance" described above. Each searcher moved back and forth to measure three distances in addition to Rd. "Head" was represented by the distance between each pair of searchers opposite each other (N vs. S, SW vs. NE, etc.) when each could just see the other's head above the vegetation or terrain. “Belt” was when each searcher could see each other’s belt area just above the vegetation or terrain. “Boots” was the most difficult to achieve consistently, with each searcher gauging when the opposite searcher’s boots were just visible. As with the Rd values, these distances were measured with the laser rangefinder (sometimes requiring multiple measurements, with propagated errors, when intervening vegetation did not obscure the target but did interfere with the laser beam) when more than the 10 m lower limit of the rangefinder, and a tape measure when less than 10 m.

For the least-square fits and ANOVA 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), except where noted below as ±propagated measurement errors. Propagation was performed using the Ludwig Maximilian University of Munich online calculator (Wienand J, http://www.julianibus.de/, last accessed Oct. 6, 2024). All tests were two-tailed, with $P<0.05$ set as the threshold for statistical significance.

Results

Rd and Head, Belt, Boots Distance Determination

Using the low- and high-vis mannequins, we determined the Rd and head, belt, boots distances as cited in Methods. The heights of the four searchers involved were 1.75 m, 1.73 m, 1.7 m, and 1.57 m (mean 1.69±0.08 m).

Mean Rd values at the Snake Hill WMA site were 21.6±5.9 m for the low-vis mannequin and 24.0±7.8 m for the high-vis. These new figures compare with 15.7±3.9 m previously measured for the low-vis mannequin at State Game Lands 203 in the summer and 34±11 m in the winter, and 27.9±8.0 m summer and 50±21 m winter for the high-vis (Fig. 2, also Chiacchia and Houlahan 2010).

We determined the head, belt, boots distances at the same locations previously used for the Rd values for SGL 203 (Chiacchia and Houlahan 2010) and the new Rd location at Snake Hill (Methods). They can be seen in Fig. 2 and Table 1. An ANOVA of the data was significant ($P<0.0001$), with the head vs. head, belt vs. belt, and boots vs. boots differences not significant between SGL 203 and Snake Hill in the summer. The significance of the other comparisons varied (Table 2), but note that the head versus belt distances were often not significantly different in the same area and season.

The standard deviation represents the variance of the head, belt, boots distances as the terrain and vegetation in a given locale and season varies. Because of this, this value does not represent the error in these distances experienced by grid searchers if they are adjusting their spacing to maintain head, belt, or boots distance. To get a sense of the other end of this spectrum — namely, perfect adjustments to keep spacing at head, belt, boots distances — we also calculated the error in these values using the limitations of the tools used to measure them (±0.5 m for the laser rangefinder, ±0.01 m for the tape measure used for distances <10 m) and propagated those errors in the averaging process. These are also shown in Table 1.

Figure 2: Head, Belt, Boots Distances (±SD)

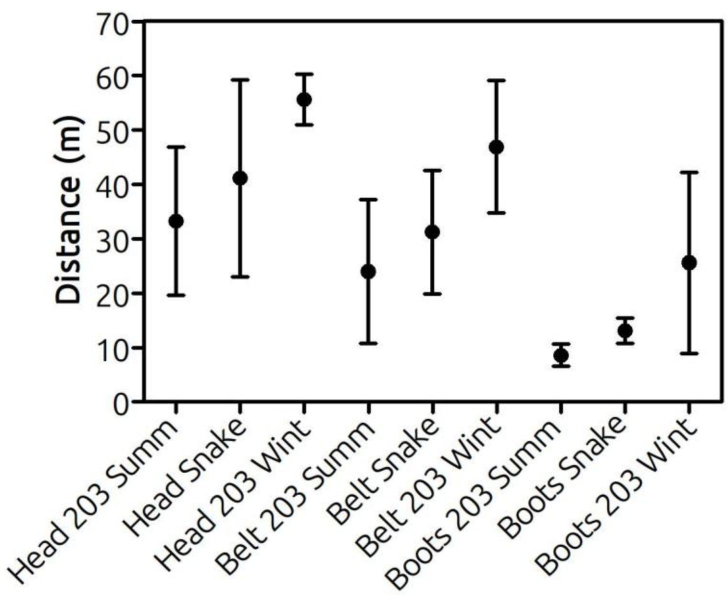


Table 1: Head, Belt, Boots Distances ± Standard Deviation vs. Propagated Error

Value	*Mean, m*	*SD*	*Propagated error*
Head Summer SGL 203	33.27	14	0.18
Belt Summer SGL 203	24.00	13	0.17
Boots Summer SGL 203	8.63	2.0	0.11
Head Winter SGL 203	55.63	4.7	0.25
Belt Winter SGL 203	46.88	12	0.23
Boots Winter SGL 203	25.63	17	0.18
Head Summer Snake Hill	41.13	18	0.35
Belt Summer Snake Hill	31.25	11	0.31
Boots Summer Snake Hill	13.13	2.3	0.25

Table 2: Tukey's Multiple Comparison Test, Head, Belt, Boots Values at SGL 203 and Snake Hill

Comparison	*Mean Diff.*	*q*	*P-value*
Head Summ vs Belt Summ	9.275	2.23	>0.05
Head Summ vs Boots Summ	24.65	5.927	<0.01
Head Summ vs Head Wint	-22.35	5.374	<0.05
Head Summ vs Belt Wint	-13.6	3.27	>0.05
Head Summ vs Boots Wint	7.65	1.839	>0.05
Head Summ vs Head Snake	-7.85	1.541	>0.05
Head Summ vs Belt Snake	2.025	0.3975	>0.05
Head Summ vs Boots Snake	20.15	3.956	>0.05
Belt Summ vs Boots Summ	15.38	3.697	>0.05
Belt Summ vs Head Wint	-31.63	7.604	<0.001
Belt Summ vs Belt Wint	-22.88	5.5	<0.01
Belt Summ vs Boots Wint	-1.625	0.3907	>0.05
Belt Summ vs Head Snake	-17.13	3.362	>0.05
Belt Summ vs Belt Snake	-7.25	1.423	>0.05
Belt Summ vs Boots Snake	10.88	2.135	>0.05
Boots Summ vs Head Wint	-47	11.3	<0.001
Boots Summ vs Belt Wint	-38.25	9.197	<0.001
Boots Summ vs Boots Wint	-17	4.087	>0.05
Boots Summ vs Head Snake	-32.5	6.38	<0.01

Comparison	*Mean Diff.*	*q*	*P-value*
Boots Summ vs Belt Snake	-22.63	4.442	>0.05
Boots Summ vs Boots Snake	-4.5	0.8834	>0.05
Head Wint vs Belt Wint	8.75	2.104	>0.05
Head Wint vs Boots Wint	30	7.213	<0.001
Head Wint vs Head Snake	14.5	2.847	>0.05
Head Wint vs Belt Snake	24.38	4.785	<0.05
Head Wint vs Boots Snake	42.5	8.343	<0.001
Belt Wint vs Boots Wint	21.25	5.109	<0.05
Belt Wint vs Head Snake	5.75	1.129	>0.05
Belt Wint vs Belt Snake	15.63	3.067	>0.05
Belt Wint vs Boots Snake	33.75	6.626	<0.001
Boots Wint vs Head Snake	-15.5	3.043	>0.05
Boots Wint vs Belt Snake	-5.625	1.104	>0.05
Boots Wint vs Boots Snake	12.5	2.454	>0.05
Head Snake vs Belt Snake	9.875	1.679	>0.05
Head Snake vs Boots Snake	28	4.76	<0.05
Belt Snake vs Boots Snake	18.13	3.081	>0.05

***W* Values for the Snake Hill WMA Exercise**

Fourteen searchers completed the Snake Hill effective sweep width exercise, with 20 real and 2 virtual DOs each on the low-visibility mannequins, and 19 real and 1 virtual DOs on the high-vis, for a total of 308 DOs for the low-vis and 280 for the high-vis. The resulting crossover-graph-based *W* values calculated by the IDEA spreadsheet were 22 m for the low-vis and 56 m for the high-vis mannequin. These compare with the *W* values predicted by the Rd measurements, 24 m and 43 m, respectively (Koester et al. 2014).

We also calculated the *W* values for the summer Snake Hill exercise using the POD-curve-based method previously described (Chiacchia and Houlahan, 2023), thus gaining parameters that could be used for statistical comparisons. These were 25.2±5.4 m for the low-vis and 68±23 m for the high-vis (Figs. 3a and b). The R-square for the fits were 0.7504 for the low-vis and 0.2941 for the high-vis mannequins; an F-test comparison of the two curves revealed a significant difference between the *W* values (P<0.0001).

The *W* values for Snake Hill compare with values of 22.5±1.9 m for the low-vis at SGL 203 in the summer (two exercises, averaged) and 53.5±8.9 m for the high-vis mannequin in the summer (Chiacchia and Houlahan, 2023).

Figure 3a: POD Curves for Determining W *Values at Snake Hill Exercise*

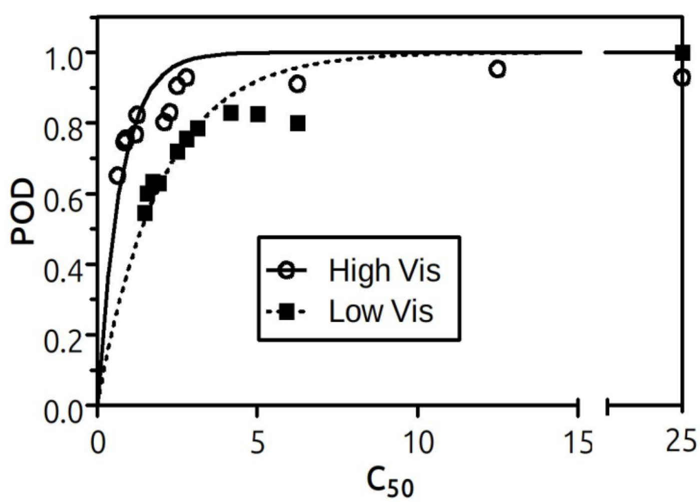
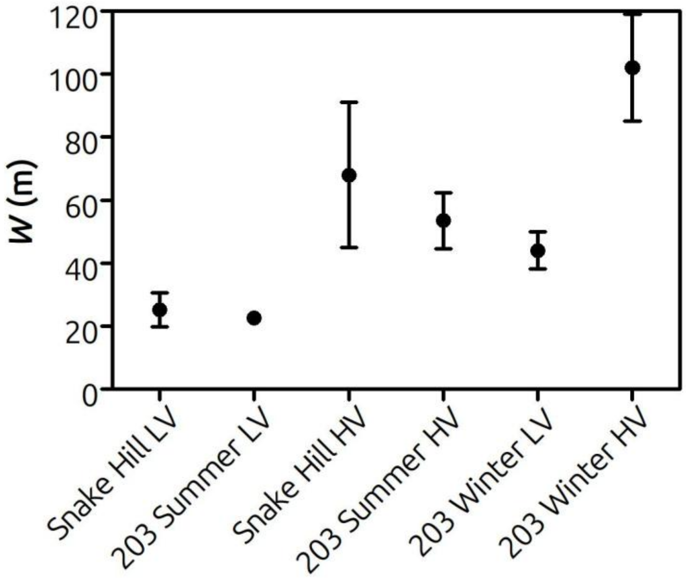


Figure 3b: W *Values for Snake Hill Exercise versus SGL 203*



A one-way ANOVA of these data, including the winter values at SGL 203 in that report (44.1±5.9 m low-vis, 102±17 m high-vis), was significant ($P<0.0001$). The post-test differences between the low-vis mannequins at Snake Hill and SGL 203 in summer as well as the high-vis at Snake Hill and SGL 203 in summer, however, were not significant. More post-test comparisons can be found in Table 3.

Table 3: Tukey's Multiple Comparison, W *Values at SGL 203 and Snake Hill*

Comparison	*Mean Diff.*	*q*	*P-value*
Snake Hill LV vs 203 Summer LV	7.7	3.043	>0.05
Snake Hill LV vs Snake Hill HV	-42.8	14.16	<0.001
Snake Hill LV vs 203 Summer HV	-28.8	9.103	<0.001
Snake Hill LV vs 203 Winter LV	-18.9	5.399	<0.05
Snake Hill LV vs 203 Winter HV	-76.4	24.15	<0.001
203 Summer LV vs Snake Hill HV	-50.5	20.6	<0.001
203 Summer LV vs 203 Summer HV	-36.5	13.91	<0.001
203 Summer LV vs 203 Winter LV	-26.6	8.804	<0.01
203 Summer LV vs 203 Winter HV	-84.1	32.06	<0.001
Snake Hill HV vs 203 Summer HV	14	4.516	>0.05
Snake Hill HV vs 203 Winter LV	23.9	6.94	<0.01
Snake Hill HV vs 203 Winter HV	-33.6	10.84	<0.001
203 Summer HV vs 203 Winter LV	9.9	2.774	>0.05
203 Summer HV vs 203 Winter HV	-47.6	14.7	<0.001
203 Winter LV vs 203 Winter HV	-57.5	16.11	<0.001

POD Values for Head, Belt, Boots Distances

Given the head, belt, or boots spacing for a grid team, the POD value for that team making one pass through a search segment, and assuming a non-overlapping pattern, the POD value can be approximated as:

6. $POD = 1 - e^{-(W/G)}$

Where G again is the spacing between individual searchers in the line (Koopman 1980, NASAR 2018, Chiacchia and Houlahan, 2023).

In this case, *W* was derived from the field sweep width experiments, and G from measuring Head, Belt, and Boot distances. We calculated the POD predicted for each of the two search objects at Snake Hill in the summer and SGL 203 in the summer and winter, propagating the errors assuming either the propagation-error-based or SD-based uncertainties described above. These values are shown in Fig. 4 and Table 4.

Figure 4: POD Values for Head, Belt, Boots Distances, Propagation-Error (black) and SD (gray) Uncertainties at State Game Lands 203 in summer and winter, and Snake Hill WMA in summer

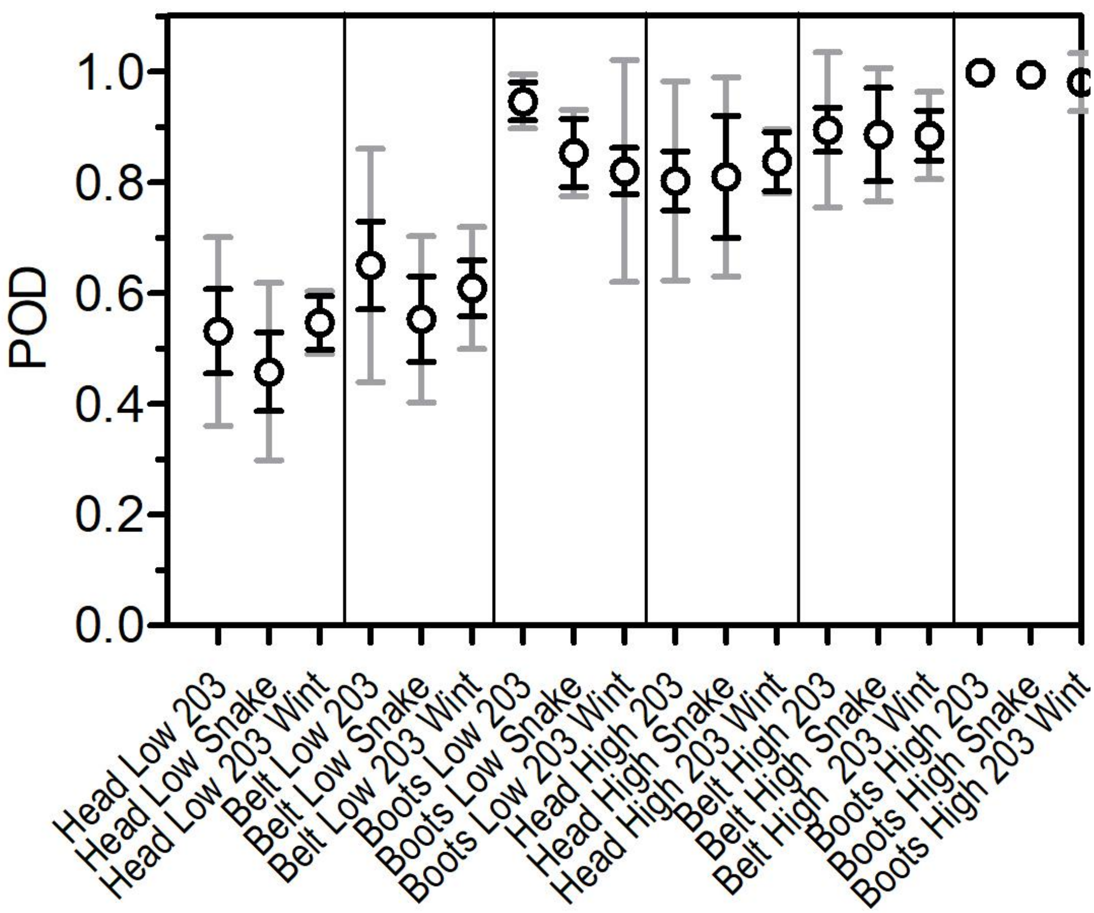


Table 4: POD Values with Propagation-Error-Based versus SD-Based Uncertainties

Search Object/Exercise	*POD*	*Propagated Error*	*SD*
Head Low 203	0.531	0.076	0.17
Head Low Snake	0.458	0.071	0.16
Head Low 203 Wint	0.547	0.048	0.057
Belt Low 203	0.650	0.079	0.21
Belt Low Snake	0.553	0.077	0.15
Belt Low 203 Wint	0.609	0.050	0.11
Boots Low 203	0.946	0.034	0.049
Boots Low Snake	0.853	0.061	0.078
Boots Low 203 Wint	0.820	0.042	0.20
Head High 203	0.803	0.053	0.18
Head High Snake	0.81	0.11	0.18
Head High 203 Wint	0.837	0.053	0.058
Belt High 203	0.895	0.040	0.14
Belt High Snake	0.886	0.084	0.12
Belt High 203 Wint	0.884	0.045	0.079
Boots High 203	0.9981	0.0020	0.0034
Boots High Snake	0.994	0.010	0.011
Boots High 203 Wint	0.981	0.014	0.052

It is not valid to use ANOVA on probabilities. However, we employed a logit transformation:

7. y = ln(POD/(1-POD))

to convert the PODs to normalized y values that could be analyzed. Using the lower, propagated-error uncertainties, a two-way ANOVA of the resulting logit values (unweighted means analysis due to the different sample sizes and the need to use values calculated from the POD-curve fit rather than repeated measurements) was significant for the column factor ($P<0.0001$), namely the difference between the different locations and seasons given the same spacing. The row factor was, not surprisingly, also significant ($P<0.0001$) — in other words, choosing head, belt, or boots spacing changes the POD. There was also a significant interaction between these two factors ($P<0.0001$).

Using a Bonferroni post-test to compare summer vs. winter at SGL 203, only the (transformed) POD values for the boots distances differed significantly (for each mannequin $P<0.001$, Table 5a). Comparing summer at SGL 203 vs. summer at Snake Hill, again only the PODs obtained at the boots distances were significantly different (for each mannequin $P<0.05$, Table 5b). The transformed PODs for summer at Snake Hill were not significantly different than for winter at SGL 203, except for the high-vis mannequin at boots distance ($P<0.05$, Table 5c). The POD values for the head or belt distances were, by this measure, unaffected by the changes in location or season (Tables 5a through c). Note, in any case, that the POD differences themselves within each spacing was almost always less than 10% — the one exception being at the boots distance in summer vs. winter at SGL 203 of 13% (see Table 4).

Table 5a: Bonferroni Post-Test of Logit Transformed PODs, Summer SGL 203 versus Summer Snake Hill

Row Factor	*Difference*	*t*	*P-value*
Low Man Head	-0.2926	0.8218	>0.05
Low Man Belt	-0.4062	1.141	>0.05
Low Man Boots	-1.105	3.104	<0.05
High Man Head	0.04729	0.1329	>0.05
High Man Belt	-0.0881	0.2475	>0.05
High Man Boots	-1.149	3.228	<0.05

Table 5b: Bonferroni Post-Test of Logit Transformed PODs, Summer SGL 203 versus Winter SGL 203

Row Factor	*Difference*	*t*	*P-value*
Low Man Head	0.06271	0.2158	>0.05
Low Man Belt	-0.1767	0.608	>0.05
Low Man Boots	-1.345	4.626	<0.001
High Man Head	0.2352	0.8093	>0.05
High Man Belt	-0.1074	0.3697	>0.05
High Man Boots	-2.338	8.044	<0.001

Table 5c: Bonferroni Post-Test of Logit Transformed PODs, Summer Snake Hill versus Winter SGL 203

Row Factor	*Difference*	*t*	*P-value*
Low Man Head	-0.3553	0.9980	>0.05
Low Man Belt	-0.2295	0.6448	>0.05
Low Man Boots	0.2396	0.6731	>0.05
High Man Head	-0.1879	0.5279	>0.05
High Man Belt	0.01934	0.05434	>0.05
High Man Boots	1.189	3.340	<0.05

Discussion

The results reported above suggest some interesting and operationally useful relationships between sight lines (represented by head, belt, boots values), the practical ability of humans to search visually in the Appalachian woods (represented by *W*), and the resulting PODs. At the simplest level, as previously reported for Pennsylvania and Ohio (Chiacchia and Scelza, 2023), the subjectively similar environment of Snake Hill WMA in the Appalachian Mountains in West Virginia and State Game Lands Number 203 on the Allegheny Plateau in Pennsylvania provide similar effective sweep width values for a given search object and season. (The vegetation in the two locations is somewhat different, the terrain almost indistinguishable.)

More provocatively, the three comparisons here (one location in summer and winter; two locations in summer; and different locations, one in summer and one in winter) suggest that the differences seen between the distances necessary for keeping sight of a neighboring searcher's head and belt (at least) and *W* values in effect cancel out in the final PODs obtained. In other words, for example, searchers spread at belt distance in an "open grid" line obtain the same PODs for a given search object (say the low-vis mannequin, standing in for a human in low-vis color clothing) regardless of location or season. This lack of statistically significant difference held despite applying the much smaller uncertainties of the propagated errors rather than SD values.

Even the statistically significant differences seen for the PODs at boots distance are unlikely to be operationally significant. The largest such difference is only 13%, comfortably less than the roughly 25% or more variation in POD seen when searchers attempting to maintain set spacing were simulated and measured (Perkins 2018) or the 25% or more errors seen when team leaders estimate POD (Koester et al. 2004). More to the point, the difference between any of the PODs measured for each distance with their mean values is well under 10% — a POD difference unlikely to drive a search effort.

Of course, we have only demonstrated the above in two subjectively similar, relatively close-by locations. It remains to be seen whether this relationship will hold in very different environments, such that "head, belt, boots" provides consistent PODs. Another caveat to the current results is that searcher height is a major affector of *W* for visual search (Koester, 2004). Given the small number of searchers involved in these exercises, particularly the heads, belts, boots measurements, we simply do not have the statistical power necessary to investigate this factor. Given the height of our searchers for the head, belt, boots measurements (1.69±0.08 m) and the average height in the United States of 1.63 m for women and 1.75 m for men (World Population Review, 2025), and the fact that our heights were not significantly different from either (one sample t-test, $P=0.251$ and 0.220, respectively), we can say that these results are likely to be typical assuming searchers are neither significantly taller nor shorter than the general population.

Digging deeper operationally, these three spacing options are not created equal. The head distance is not particularly practical. While it covers more ground, it's not much farther than the belt distance. Worse, when keeping neighboring searchers' heads just in sight, we run the risk of losing sight of them entirely. This, as stated in the Introduction, creates a situation in which we have become unaware of how big the gap has become, and we risk losing operational cohesion for the grid team.

The boots distance suffers from a different issue. As we said above in most searches, our imperative is to balance speed with thoroughness. Boots achieves thoroughness at the expense of placing searchers so close together that they will not cover much area very quickly; PODs will be high, but again we risk lingering in an area that does not contain the subject. We also found that, in practice, boots distance was difficult to define as exactly as the others, which may have contributed to the fact that this distance was the only one to show a significant P-value for the same search object between the seasons and locations.

The belt distance may represent exactly the kind of speed/thoroughness balance we desire. From our results we would expect it to produce a POD of 55-65% for prone subjects in low-visibility clothing and a little under 90% for subjects in high-vis. These are quite serviceable PODs, particularly when this spacing allows a six-member grid team to sweep a roughly 120 to 240 m front for each pass through an area, depending on season. Should these consistent PODs prove to result in a wider variety of environments, our recommendation would be for belts to be the standard spacing for open grid teams.

Crucially, the head, belt, boots method provides objective advantages compared with virtually all the other methods for spacing searchers (specifically, "keeping in sight," rain dance, Rd spacing, and specific spacing based on known *W*). Specifically, it provides a demonstrably more accurate POD (particularly compared with "in sight" and rain dance) and requires less divided attention from searchers (compared with rain dance, Rd, and specific spacing) than the other methods. Divided attention is of particular concern in translating performance of searchers in exercises to that in the field in real deployments.

A word should be given for the so-called "purposeful wandering" technique (NASAR 2018). Intended to improve searchers' performance, it consists of having searchers wander within a given envelope (most often defined by Rd) to search under, behind, and among vegetation, rocks, and terrain. It undoubtedly increases POD, but perhaps not by improving *W*, as is often assumed. Note purposeful wandering differs from the dynamic distancing in heads, belts, boots as it does not involve a well-defined target and can open up spaces between searchers in a way that heads, belts, boots does not.

Clearly, by increasing searchers' paths walked through the area, it causes them to linger, which will increase POD. But we cannot move toward a spot without moving away from another spot. This is critical, as searchers in practice tend to use purposeful wandering to look in places that are otherwise difficult to see into, not necessarily places in which the subject is more likely to *be*. This is a problem if there is a mismatch between the two. Equating them may be valid for an evasive subject, but if the subject is not trying to hide, purposeful wandering could cause us to miss subjects who are *not* in difficult places.

Purposeful wandering may also subvert search planning's intentions for a given search task. As the POA values used to determine where to task teams are based on statistical behavior, they can never be more than an estimate and may be quite inaccurate for a given, if outlying, search subject. Thus, as described above we must aim for a "Goldilocks" level of search that is neither too thorough nor too fast, to avoid lingering in empty areas or missing a subject in the area being searched, respectively. By increasing linger, purposeful wandering tends to push all search efforts toward high thoroughness, low speed, when we need to balance the two.

Finally, purposeful wandering takes the problem of maintaining searcher spacing at arbitrary distances and scrambles it. With searchers wandering, the theoretical Rd envelope is in practice impossible to maintain, as searchers must both memorize a target distance *and* the deviation from that distance produced by wandering. With all the above taken into consideration, the authors would not recommend the use of purposeful wandering at all in human visual grid search.

At the National Association for Search and Rescue annual conference in San Diego in 2005, one of us (KBC) had the opportunity to see Robert Koester present his and his colleagues' initial findings (Koester et al. 2004) on how to measure effective sweep width in the ground-search environment. The method clearly offered a means to achieving objective PODs in the field; but it was not received well by all attendees. Some were dismayed by the observation (since replicated, including by us) that SAR training and experience do not seem to improve the sweep widths achieved by searchers. These attendees' accusation at the time was that the work was devaluing trained searchers and their necessity to a successful search effort.

Even at the time, the author realized that there is much that trained, professional searchers, paid or volunteer, offer searches beyond placing eyes on targets. These include navigation, field team leadership, incident management, communications, and many other factors needed to make searches more successful. Nonetheless, effective sweep width findings do suggest that untrained local volunteers are as useful at the *seeing* part as trained searchers, particularly when led by the latter. Combined with the worsening sparsity of volunteers for public safety organizations, the results suggested a new paradigm in which we train SAR responders not to be *searchers*, but to be search *leaders*. To some extent, this paradigm has been adopted.

The current findings add a potentially important nuance. The rather large SD-based uncertainties seen in Fig. 4 above represent the inconsistency we would see in POD if we spaced our searchers at a given distance and had them walk in perfectly straight lines through the area, regardless of changes in terrain or vegetation. The considerably smaller propagated errors, on the other hand, represent our searchers spacing themselves at that distance and then using their neighbors' heads, belts, or boots to adjust to changes in terrain or vegetation perfectly, so that those target points of anatomy remain just visible.

Clearly, all the training in the world will not allow searchers to adjust their spacing with such perfection. But arguably this represents a training *target*. More importantly, we would expect trained searchers to differ from emergent volunteers by achieving spacing consistency *closer* to that target. Part of the value of search training may be about moving from the inconsistency of the SD errors toward the tighter propagated errors, and may offer a way in which trained searchers are more *consistent* at searching than emergent volunteers, in addition to offering the other SAR skillsets.

Limitations of the Current Study

The limits previously discussed (Chiacchia and Houlahan 2023) of using mannequins to stand in for prone humans, while probably not a major factor, still apply. More significant is the question of whether adding additional members to a search team over a single searcher, which is what we measured here, will truly increase the team's effective sweep width in an additive manner. This question merits future study.

This report compared the PODs expected from heads, belt, and boots spacing in one location in two seasons, and two locations in the same season. As cited above, this is a small sampling and will need to be replicated, particularly in different environments that are less similar.

Possibly the most speculative element to this report is the use of propagated measurement errors rather than standard deviations in ANOVA tests. While our reasons for doing so are, we believe, valid and described above, it may affect the accuracy of the P-values derived. However, again as outlined above, the standard deviations of the head, belt, boots distances are unlikely to represent the variance in POD of a team adjusting their spacing to maintain a given target distance. Moreover, because these SDs are so much larger than the propagated errors, the stated aim of our report — to determine whether the PODs at a given distance are *not* significantly affected by locale or season — would have been trivial using the larger SDs. We used the propagated errors as a more rigorous test of these similarities.

Another issue, with the two-way ANOVA in the transformed POD comparison, was the significant interaction P-value. Interaction makes significance in the column or row factors difficult to interpret; in this case, the significant differences between the boots POD values, while the differences between the heads and belts PODs were not significant, are interesting but not likely to be operationally significant due to the reasons offered above. Also contributing to the difficulty of interpreting this result precisely was the unweighted means analysis necessitated by different sample sizes re. the head, belt, boots measurements as well as deriving uncertainty parameters from a fit instead of multiple measurements.

Finally, our discussion of the meanings of the propagated versus SD variances, while we believe to be justified, is somewhat speculative. Measurement of the actual variance in POD performance versus training level of searchers (bearing in mind that we do not expect the PODs themselves to be significantly different based on SAR experience, Koester et al. 2004, Chiacchia and Houlahan 2010) will be necessary to assess this prediction.

Conclusions

A key lost-person search method is the “grid team,” a line of searchers moving abreast through the woods. The optimum spacing for such searchers is not clear, however. We have determined the spacing necessary for searchers to see their immediate neighbors’ head, belt, or boots at sites in West Virginia in the summer and in Pennsylvania in the summer and winter. An analysis of the probabilities of detection expected from previously or newly measured effective sweep width values in those locations for each of these spacings suggests that each spacing offers a consistent and useful POD for a given search object that does not appear to be affected by location or season by an operationally significant amount.

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Abbreviations

Rd: Radius of detection, the mean distance at which an observer cued to the location of an object can detect it when moving toward 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 50 m.

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.

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