Incorporating Ocean-Borne Debris Information into Search Object Location Distributions

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Abstract

This paper presents a method for incorporating information from waterborne debris that has been recovered at a known time and place into the object location distribution. The method involves calculating a likelihood function which can be combined with the prior distribution on the location of a lost object, such as a ship or aircraft lost at sea, to produce, in a Bayesian fashion, a posterior distribution that reduces uncertainty in the location of the loss. When the search operation involves a person or vessel adrift at sea, incorporating debris information in this fashion will allow the search planner to produce better predictions for the location of the search object at times of future searches and enable more effective deployment of search assets. Use of this method will save time, money, and lives.

KEY WORDS: *Maritime Search and Rescue*, *Ocean-Borne Debris, Maritime Loss, Debris Drift, Object Location Distribution, Bayesian, Posterior Distribution*

Introduction

Despite the considerable communications technology and capabilities available to most vessels and aircraft today, there are still incidents where they are lost at sea without anyone receiving a distress call from them. In such situations, the realization that the craft is missing may not occur until it becomes overdue at its destination. This will delay the initiation of search efforts. Once a search is undertaken, the first objects found are likely to be floating debris that was left on the surface and drifted away from the accident site due to winds and currents. When this happens, the first question is, “Where could this debris have come from?” to be quickly followed by, “Within the ‘possibility area,’ which locations are more likely and which are less likely to have been the source of this debris?" Accident investigators may want to locate the sunken wreckage, especially if recording devices were being carried. If there is the possibility of survivors (which often follow drift trajectories different from debris), search and rescue (SAR) authorities will want to know the location of the incident so they can develop better estimates of where survivors adrift will most likely be located when SAR assets can be on scene searching.

The present simplistic method of incorporating debris information into an object location distribution involves performing a "reverse drift" on pieces of debris from the time and place of recovery to the time of the distress. In the US Coast Guard's Search and Rescue Optimal Planning System (SAROPS), Kratzke et al (2010), this requires the user to specify uncertainties in the wind and ocean current estimates and run the SAROPS drift system backward in time using the negative of the estimated wind and current velocities. There are several difficulties with this method. First, reverse drift models are not well tested and validated. Second, the resulting reverse drift location distributions tend to have very large uncertainties (spreads) if the debris is found more than one or two days after the time of the distress. As a result, the reverse drift distribution often provides very little information about the location of the distress. Finally, a better way to incorporate this information is to apply Bayesian inference – a widely used method for adjusting prior probability estimates based on subsequently discovered evidence.

In the first section below, we show two examples of reverse drift distributions produced for the Air France Flight 447 search in 2009 -2011. Debris from the AF447 search was first recovered six days after the plane crashed into the ocean. The first example shows the large uncertainties produced in the reverse drift distribution from these debris using the SAROPS method. This estimate provided very little additional information about the location of the aircraft wreckage. The second example shows a reverse drift distribution that did not correctly account for wind and current uncertainties and that produced a very poor estimate which resulted in a year of wasted search effort.

In the second section below, we describe our proposed method of incorporating debris information. It uses forward drift predictions and constructs the likelihood function for this information which allows us to combine this information in a Bayesian fashion with the prior distribution to produce a posterior distribution and reduce the uncertainty in the object location. We illustrate the power of this method by showing how it was used to incorporate information from a piece of debris from the Malaysian Airlines Flight MH370 crash found on Reunion Island. In this example we see that this debris information reduced the uncertainty in the object location distribution even though it was found more than a year after the loss. The third section compares the reverse drift and forward drift methods of incorporating debris information.

The MH370 example involves search for stationary target. However, in the fourth section below, we show how this forward-drift method can be applied to search objects that are moving such as survivors adrift in a lifeboat. In the fifth, we show how to apply the forward drift method when the time of loss or distress is uncertain.

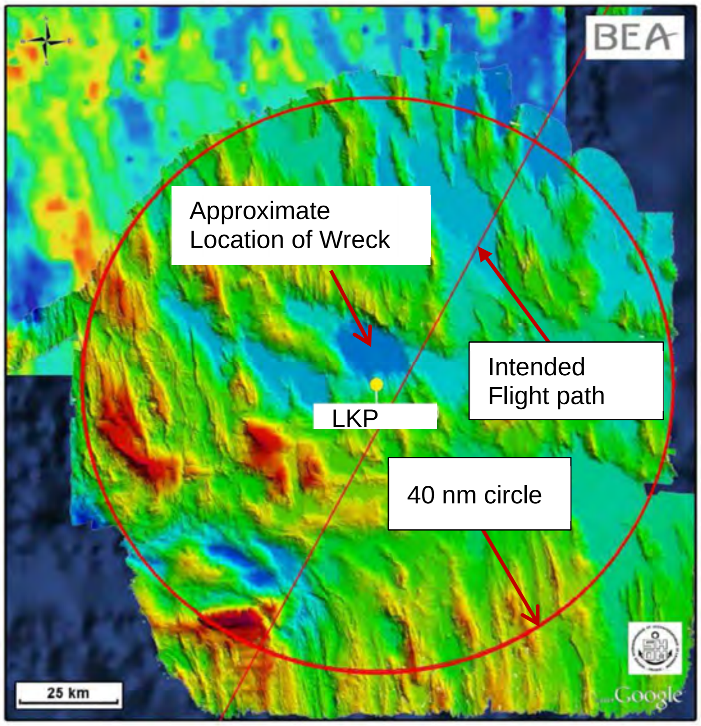
Reverse Drift Examples

In the early morning hours of June 1, 2009, Air France Flight AF447 from Rio de Janeiro to Paris disappeared during stormy weather over the Atlantic with 228 passengers and crew aboard. Figure 1 shows the last known position (LKP) of AF447.

Figure 1. Last known position (LKP) for AF447, 2.98°N, 30.59°W

At dawn a surface search for survivors and wreckage began. On June 6 the first bodies and floating debris were found 38 nautical miles (nm) north of the LKP. The French Bureau of Enquiries and Analysis (BEA) took charge of the search and estimated that the plane must have crashed within 40 nm of the LKP as shown in Figure 2.

Figure 2. 40 nm circle about LKP



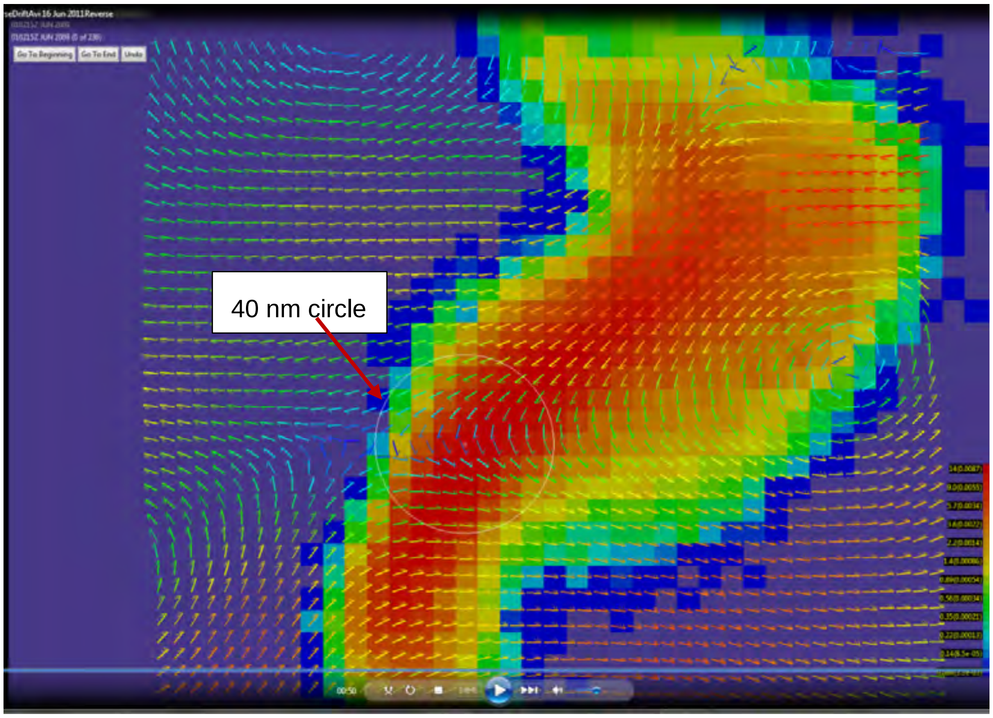
An intense acoustic search was performed to detect the underwater locator beacons (ULB) attached to the flight data recorder and cockpit voice recorder. This search was unsuccessful. The following year an intensive sonar search was performed based on a faulty reverse drift analysis by a group of oceanographers called the drift group. This search was also unsuccessful. In 2010, after two years of unsuccessful search, Metron was tasked by the BEA to compute a probability map for the location of the wreck using all available information including unsuccessful search as well as recovered bodies and debris. On April 8, 2011, BEA issued the following statement

> *This [Metron] study, published on the BEA website 20 January 2011, indicated a strong possibility for the discovery of the wreckage near the center of the [40 nm] Circle. It was in this area that it was in fact discovered after one week of exploration.*
> —— Trodec (2011).

SAROPS Reverse Drift for AF447 Distribution.

One piece of information that Metron used to construct its probability map was the set of positions and times at which 33 bodies were recovered from 6-10 June 2009. The positions of these bodies were drifted back to the time of crash using the best wind and current estimates available to us for the time and place of the crash. We used the SAROPS reverse drift methodology with our best estimate of the uncertainty in the wind and current estimates. The result of this was a distribution with an extremely large spread extending far beyond the 40 nm circle as shown in Figure 3. This was not very helpful in locating the wreck.

Figure 3. Reverse drift distribution. The 40 nm circle is shown as a thin yellow line. Vectors indicate the estimated direction of the surface currents at the time of the cash

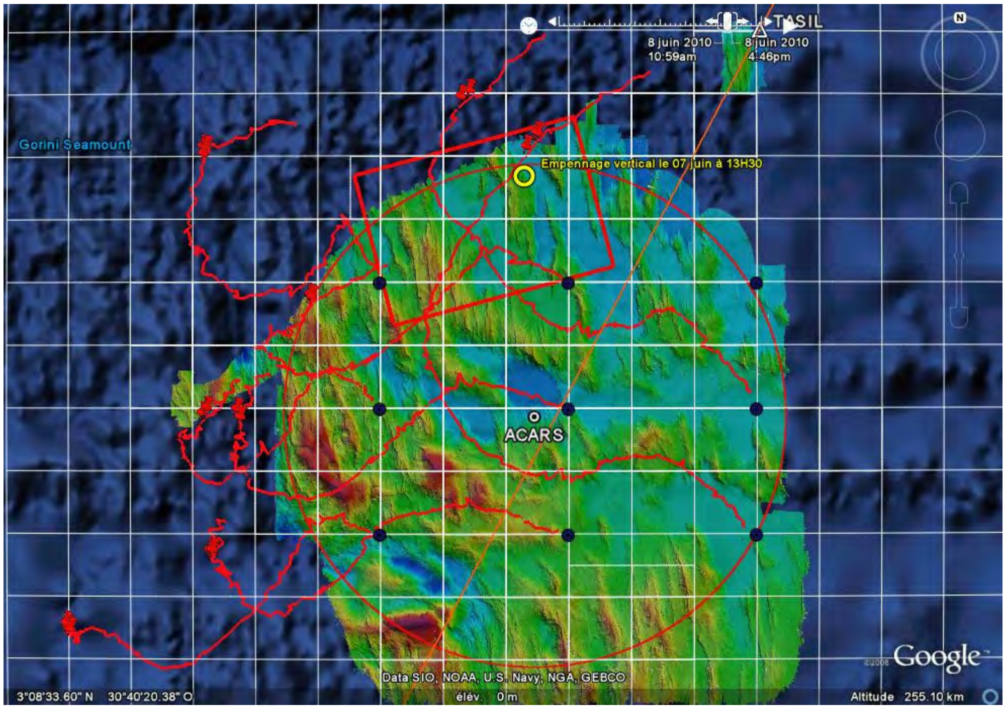


Drift Group's Reverse Drift Distribution

Over the winter of 2009-10, the BEA assembled a team of distinguished oceanographers (the drift group) and tasked them to produce a reverse drift distribution for the location of wreck. They used data from Argo floats, NOAA's Atlantic Oceanographic and Meteorological Laboratory surface drifters, and fishing buoys drifting in the area at the time of crash to inform their current models. Using these models, they performed a reverse drift of the positions of the recovered bodies and debris found on June 6 and 7 back to the time of the crash. They took the average of the "most consistent" predictions to obtain the rectangle shown in Figure *4* which they claimed was a 95% containment region for the location of the wreck. The search in the summer of 2010 was based on this rectangle and was unsuccessful. There are a number of methodological errors in this approach, but the main ones are (1) the failure to properly incorporate the uncertainty in their predictions into their estimate of the location of the wreck and (2) the removal of predictions that were "inconsistent" with the majority of the predictions.

The drift group's prediction also violated one of the cardinal rules of search planning – namely use all available information when forming estimates of the search object's possible/probable locations during the next search. In the fall of 2010, the BEA asked Metron to produce a probability map for the location of the wreck over the winter of 2010-11 using all available information. This effort produced the probability map that the led to finding the wreck within days of resuming the search in the spring of 2011.

Figure 4. The red rectangle is the 95% containment region estimated by the drift group. The circle is the 40 nm circle. The "wiggly" lines are the paths of 8 data buoys placed inside the 40 nm circle on June 3, 2010 and allowed to drift for 6 days. The wildly different paths of these buoys illustrate the complexity of the ocean currents in the search area.



Forward Drift Method

This section describes a Bayesian method for incorporating debris information into the probability distribution for a search object whether it is stationary or moving.

Likelihood Function for Recovered Debris

Suppose a vessel or aircraft is presumed sunk in the ocean, and we are uncertain about its location. Suppose that a piece of floating debris is recovered at a location y at time T after the loss and that it is determined that the debris came from this craft. If we have a model for debris movement in the vicinity of the loss over the time during which the piece of debris floated on the water, we can use this model to compute a likelihood function for the location of the loss. This likelihood function can be combined with the prior distribution on the location of the loss to compute a posterior distribution for the loss location. In this Bayesian fashion, the posterior will incorporate the information from the debris recovery into the estimate of the location of the loss. As more debris is found, this process can be iterated to refine the posterior probability estimate of the source location.

Computing the Likelihood Function. For convenience, we impose a grid of cells on the ocean area of interest indexed by $j=1,\ldots,J$. Let $p(j)\geq 0$ be the prior (before incorporation of the debris information) probability of the vessel being located in cell j. We assume that

$$\sum_{j=1}^{J} p(j)=1. \tag{1}$$

The observation (y,T) is the location and time (after loss) of the recovery of the debris. The likelihood function L for this observation is defined as follows.

$$L\big((y,T)\,|\,j\big)=\Pr\{\text{Debris floated to position } y \text{ over time } T \,|\, \text{ it originated in cell } j\}. \tag{2}$$

Note that the observation (y,T) is fixed or known. The cell j is variable or unknown. As a result, the likelihood L is a function of j. This function need not be a probability distribution on the set of cells $j=1,\ldots,J$, i.e., it may not sum to 1. It gives the relative likelihood of the various candidate cells being the origin of the piece of debris.

Using a model of winds and currents plus leeway assumptions, one can perform the following set of experiments to estimate the likelihood function in (2). Designate a region R around the point y. The size of this region is somewhat arbitrary but it should be large enough to capture a reasonable sample of the drift particles used to estimate L. For each cell j in the prior distribution, generate a large number N of initial points in that cell and drift them for time T using independent draws from the statistics of the ocean currents and winds to produce N drift paths. Calculate the number n_j of paths that enter R over time T. Then

$$L\big((y,T)\,|\,j\big)\approx\frac{n_j}{N} \tag{3}$$

is an estimate of $L\big((y,T)\,|\,j\big)$ for $j=1,\ldots,J$.

Computing the posterior. Using Bayes rule, it is now straight-forward to compute the posterior distribution for the location of the loss. It is given by

$$\tilde{p}(j)=\frac{L\big((y,T)\,|\,j\big)\,p(j)}{\sum_{j'=1}^{J}L\big((y,T)\,|\,j'\big)\,p(j')} \text{ for } j=1,\ldots,J. \tag{4}$$

MH370 Example

This example is taken from a Metron technical paper by Gurley and Stone (2015) written shortly after the first piece of debris, a flaperon from the wing of MH370 (Figure 5), was found on Reunion Island (Figure 6) off the East Coast of Africa more than a year after the crash. The paper developed the forward-drift likelihood function method of incorporating debris information and applied it to the MH 370 flaperon found on Reunion Island. At the time the paper was written, the authors did not have detailed information about the prior probability distribution being used by the Australian Air Transport Safety

Board (ATSB) to plan their search, so they relied on public statements and press releases to approximate this distribution. They also had to rely on a publicly available and somewhat coarse-grained model for ocean currents, and they did not account for the possible effects of wind (leeway) on the flaperon. Nonetheless, the example and analysis summarized below show that incorporating this debris information produced a significant shift to the north of the location distribution for the MH370 crash. Details of the analysis are given in Gurley and Stone (2015).

Figure 5. Flaperon found on Reunion Island 29 July 2015

Figure 6. Reunion Island

An extensive analysis (ATSB (2016) and Davey et al (2016)) performed by the Australian Defence Science and Technology (DST) Group in 2016 used more detailed modelling of ocean currents, a model for the leeway of the flaperon, and the forward-drift likelihood method of the paper to produce a similar analysis using the flaperon and other debris recovered from MH370. The overall conclusion was the same. The probability distribution for the location of MH370 was shifted to the North as a result of incorporating the debris information.

Forward-drift likelihood example

Gurley and Stone demonstrated the forward-drift likelihood method by generating a 2-dimensional posterior probability map for the location of the MH370 that incorporated their best estimate of the prior probability distribution for MH370 based on public statements from senior ATSB officials directing the search operation. They computed a 2-dimensional likelihood function using the information from the recovery of the flaperon on Reunion Island and a general, long timescale, probabilistic debris transport model for the drift model for the debris.

Ocean drift simulation

van Sebille et al (2012) used multiple decades of ocean drifter buoy trajectory data from the Global Drifter Program to generate a transport model that captures the observed dynamics of ocean circulation on global and regional scales. Their approach models ocean debris movement as a discrete-time Markov chain process where the transition matrix $\mathbf{T}$ represents the probability of debris movement from any grid cell to any other grid cell at each time step. Based on the ocean drifter buoy data, van Sebille empirically derived $\mathbf{T}$ for a global $1^{\mathrm{o}}\,x\,1^{\mathrm{o}}$ grid at $\Delta t = 60$ days. To capture seasonal variability, van Sebille derived separate bimonthly values for $\mathbf{T}$ by analyzing observations over 2-month windows throughout the year. Specifically, they estimated $\mathbf{T}_{\text{Jan-Feb}}, \mathbf{T}_{\text{Mar-Apr}}, \text{ etc}$. From these transition matrices, the probability distribution of debris can be computed by iterating the equation

$$p_{t+60\text{ days}} = p_t \mathbf{T}_m \text{ where } m \text{ is the bi-month index corresponding to starting time } t \qquad (5)$$

and p_t is the row vector of probabilities in cells for the location of the debris at day t.

There are several assumptions implicit in this approach. First, we assume that the ocean drifter buoy trajectory observations that are the basis of the transition matrices $\mathbf{T}_i$ adequately approximate the general movement of a debris field in the open ocean. No attempt is made to perform high-resolution modelling of separate wind and current forcing or leeway modelling to predict the resultant differential movement due to the different sizes of individual pieces of debris. van Sebille notes that while all the drifting buoys were deployed with drogues at 15m depth, approximately 52% lost their drogues during their reporting life. Therefore, the observation set is a random mix of objects impacted by wind and current forcing (buoys without drogues) and objects impacted by current forcing only (buoys with drogues). This closely approximates the mix of debris typically found at sea (van Sebille et al (2012)): some objects at the surface are subject to wind forcing and some are near-neutrally buoyant just below the surface not impacted by wind forcing. Second, the van Sebille model conserves mass. It assumes that all initial drift particles remain in circulation: all coasts are hard boundaries, so nothing washes ashore, and nothing sinks.

Under the limits described above, Gurley and Stone used this model to estimate gross debris drift patterns over a 480 day period starting in March 2014 varying the source location across the ATSB MH370 Wide Search Area region (MH370 (2014)). For their analysis, they considered the arc segment bounded by -15.3 ^{o} and -40 ^{o} to provide sufficient buffer both north and south for the prior distribution. The width of the region is $\pm$ 125nm normal to the arc at each point which is the maximum distance from the arc that ATSB considered across all their end-of-flight scenarios (see Table 1 of ATSB (2014)). These parameters define an annulus sector on the earth's surface. Since all the subsequent analysis was conducted on the $1^{o}\,x\,1^{o}$ latitude/longitude grid used in the debris transport model, the final set of grid cells examined as possible source areas is the intersection of the regular $1^{o}\,x\,1^{o}$ grid and the defined annulus sector. This yielded 213 candidate grid cells as shown in Figure 7.

Figure 7. MH370 Wide Search Area grid cells (blue) used for candidate source locations

At simulation start, debris were uniformly distributed across a $3^{o}\,x\,3^{o}$ box centered at each of the 213 candidate source cells. Debris movement was then drifted forward eight time-steps (480 days) starting in March 2014. Examples are shown in Figure 8.

Likelihood Function Estimation. To estimate the likelihood function $L\left((y,T)\,|\,j\right)$, they designated a sink region around y, and for each of the 213 candidate source cells, they accumulated all particles that arrived at y during any time step up to the end time T. Let $n(y,t,j)$ be the number of particles that arrived in the sink region at time t from source cell j for $j=1,\ldots,213$. Following (3)

$$L\left((y,T)\,|\,j\right)\approx\frac{1}{N}\sum_{t=0}^{T}n(y,t,j)\ \text{ for }\ j=1,\ldots,213. \qquad (6)$$

Since the van Sebille model is mass conserving, all particles entering the sink region y are removed from the general population at the time step at which they enter the region. This prevents double counting during subsequent time steps. The sink region was modeled as a $3^{o}\,x\,3^{o}$ box centered on Reunion Island (-21,56). The resulting estimate of $L\left((y,T)\,|\,j\right)$ is shown in Figure 9 for all 213 cells that comprise the MH370 source set.

Figure 8.Probability distribution of debris after a 480-day drift simulation for sample northern (top) and southern (bottom) source regions within MH370 Wide Search Area zone. Source region for each is shown as a black box. Red is 0.002

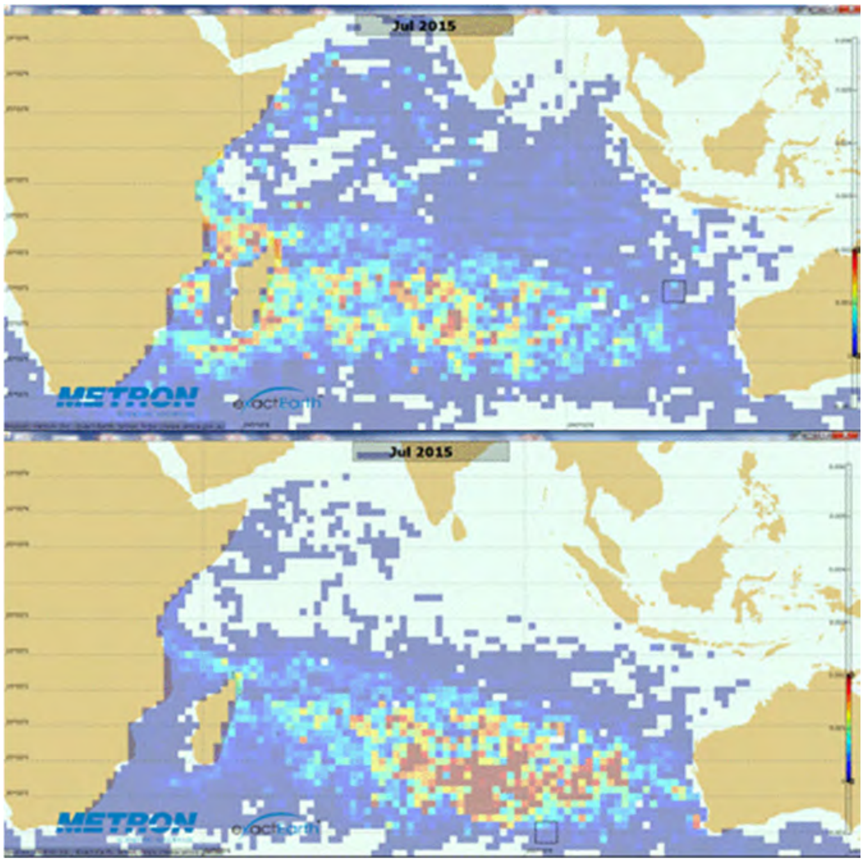
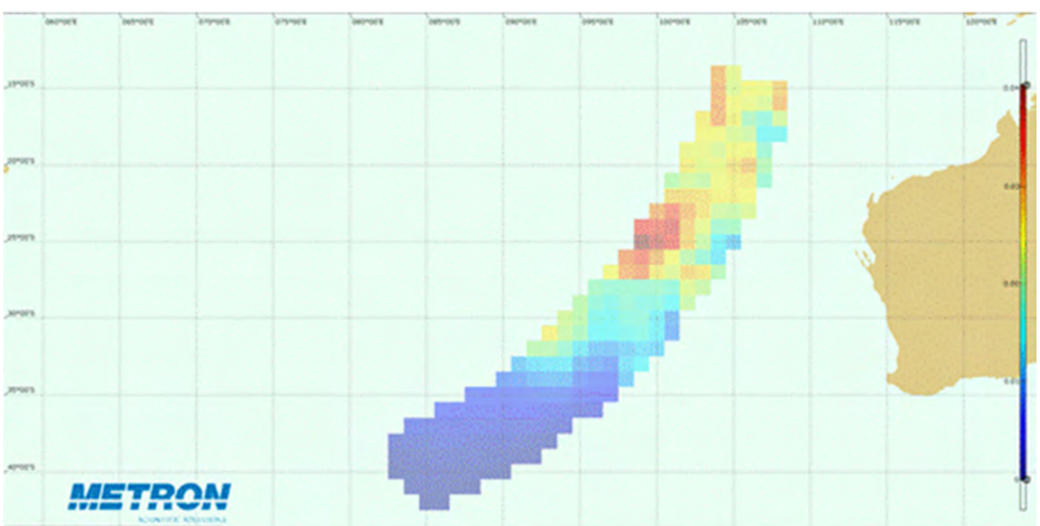


Figure 9. Estimate of likelihood function for the MH370 flaperon found on Reunion Island as a function of source region location. Red is 0.04.

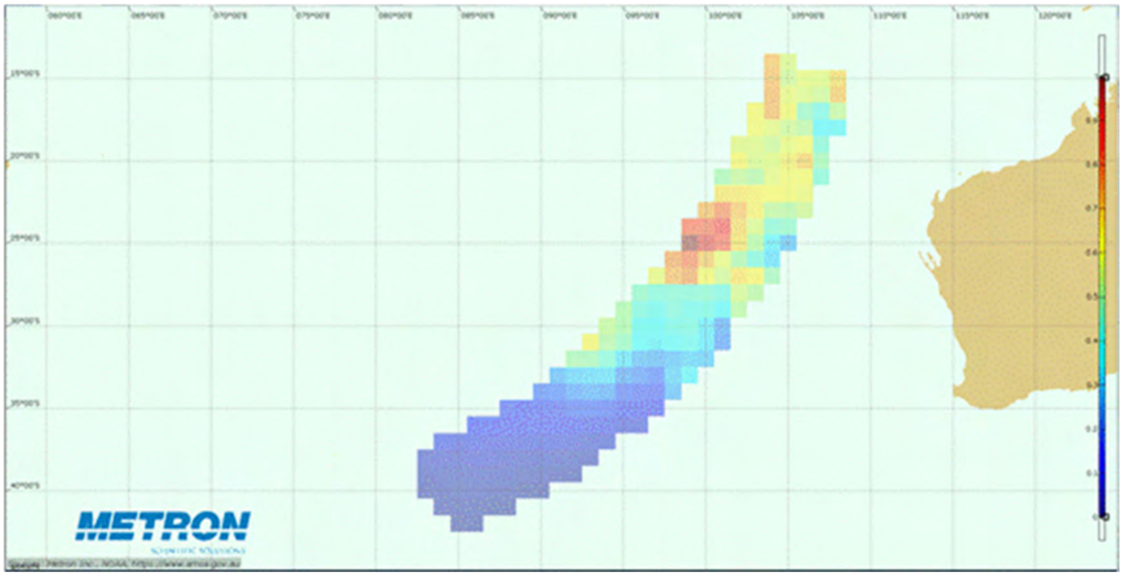


To better illustrate the spatial distribution of relative values across all the possible source grids, the ratio

$$\Lambda((y,T)\mid j) = L((y,T)\mid j) / \max_{j} L((y,T)\mid j)$$

is shown in Figure 10. This indicates that cells in the northern portion of the MH370 Wide Search Area are ~10 times more likely to be the source location than cells in the southern portion.

Figure 10. Ratio of source cell likelihood to maximum likelihood cell on a 0 to 1 scale.



Prior and Posterior Distributions

Gurley and Stone then attempted to estimate the prior probability distribution in use by the MH370 search team (in 2015) based on the published ATSB reports and public statements from Australian officials. Their focused search zone had progressively shifted to the more southern areas of the Wide Area Search region over 2014-2015, and statements in 2015 from senior government officials describe a very high certainty that the MH370 impact zone was in the extreme southern portion of the Wide Area Search region.[1] Based on a review of the ATSB operational reports, the area they have concentrated on is roughly bounded by the latitudes -32° to -39°. While there isn't enough information in the available ATSB reports to explicitly calculate the prior probability distribution or to assess the source of ATSB's certainty in their assumptions, Gurley and Stone approximated the general shape of the prior probability distribution that is the basis for the ATSB planning.

The paper modeled the prior distribution on the location as a product of independent distributions on two components, distance normal to the arc centerline and distance along the arc centerline from -40°. The paper gave the first component a normal distribution and the second component a gamma distribution with $\alpha = 5.8, \beta = 1$. This gamma distribution has the desired properties of quickly going to

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[1] Australian Deputy Prime Minister was quoted in Wall Street Journal Article on 04 August 2015 saying that "The experts are telling us that there is a 97% possibility that it [MH370] is in that area [current search area] and if you move into a wider area there is just too much to be covered for a small chance of finding the aircraft."

zero immediately to the left (south) of the peak, concentrating about 95% of the probability in the region between -39 ^{o} and -32 ^{o} and retaining a more gradual tail to the right (north) of the peak. The normal component is modeled by a Gaussian distribution with mean 0 and $\sigma =$ 50km (27nm). The resulting prior and posterior probability distributions are shown in Figure 11 and Figure 12. The change in probability in each cell from Figure 11 to Figure 12 is due to including the information about the discovery of the flaperon on Reunion Island is $\Delta p(j) = \tilde{p}(j) - p(j)$ which is shown in Figure 13. This figure shows the regions that have increased (red) or decreased (blue) in probability of being the MH370 impact site location based on the flaperon discovery. Figure 13 shows a clear shift of the posterior distribution to the north reflecting the effect of applying the debris likelihood function.

Figure 11. Bivariate prior probability distribution. Max scale (red) is 0.02.

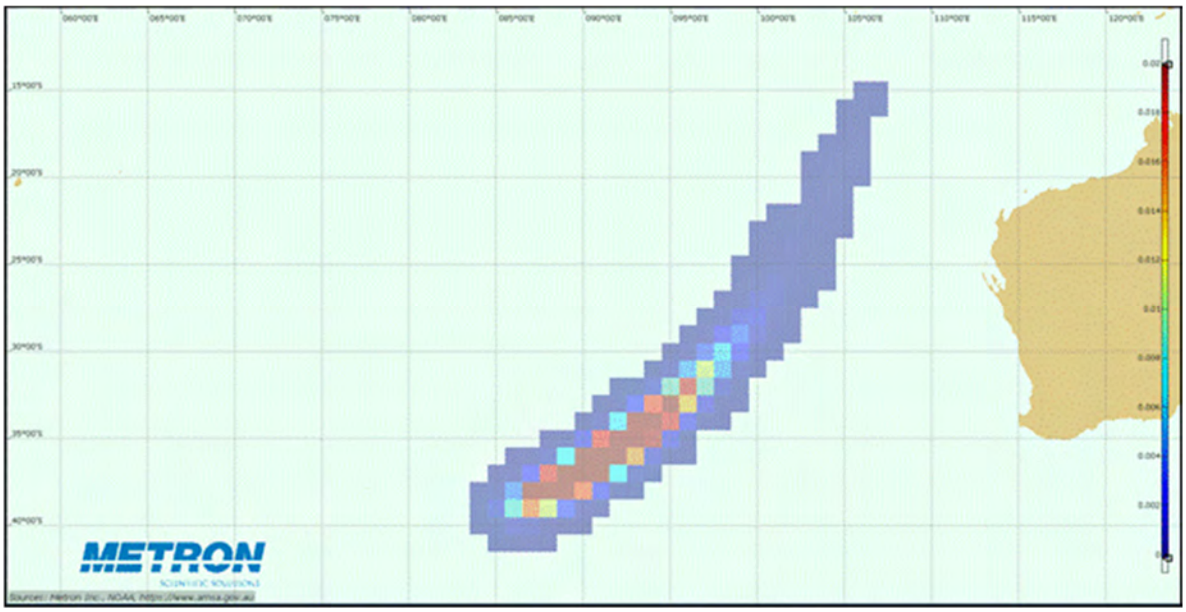


Figure 12. Posterior probability distribution. Max scale (red) is 0.02.

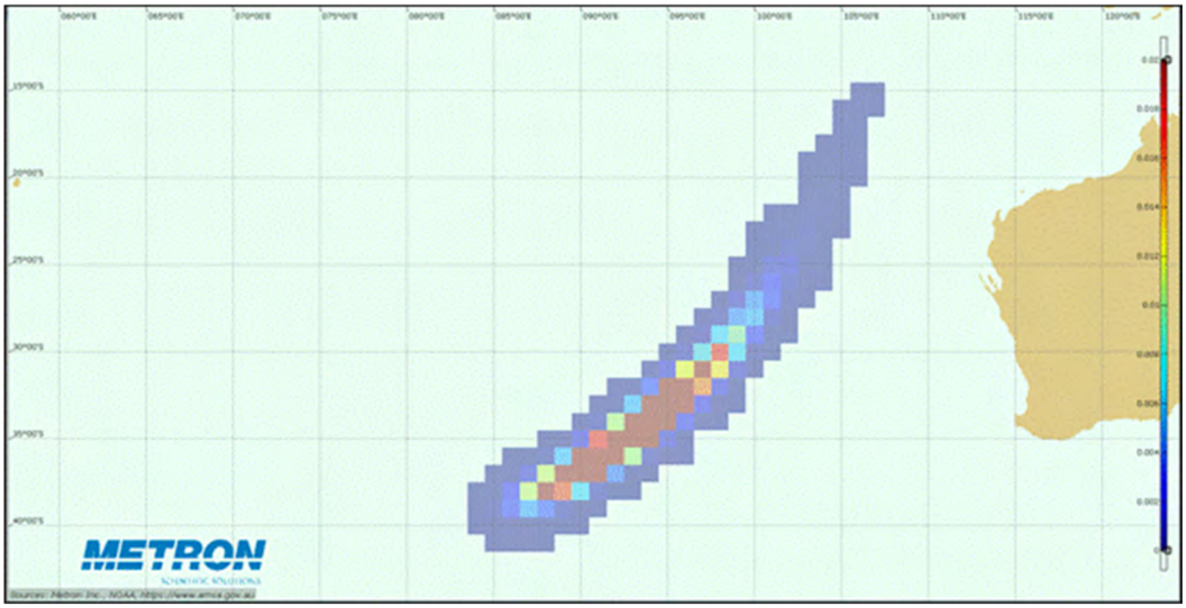
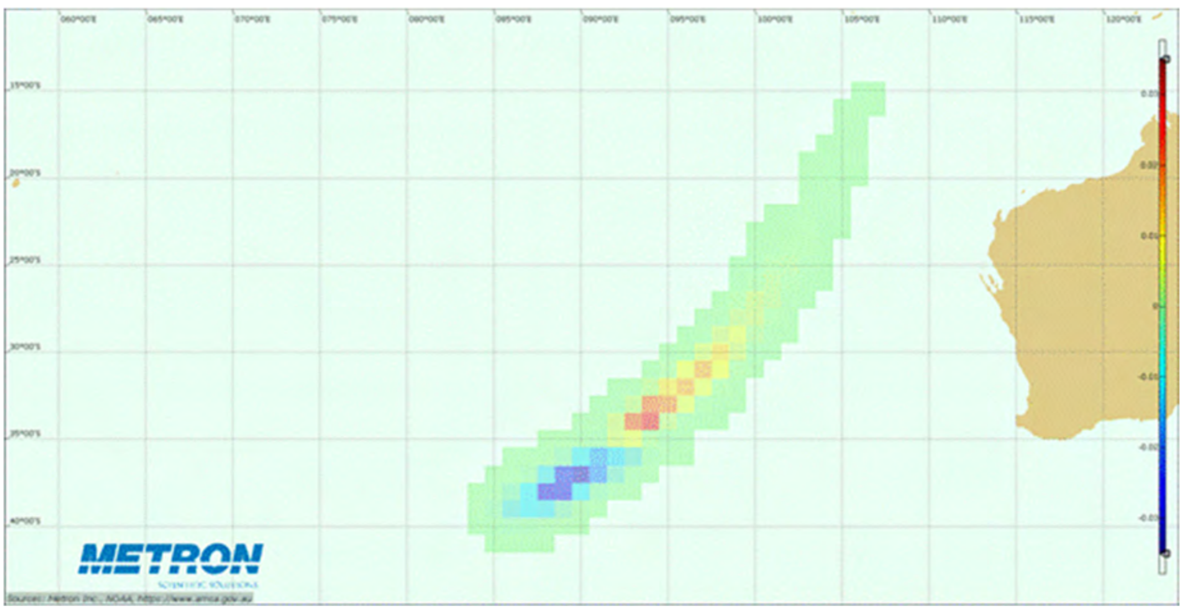


Figure 13. Change in probability distribution of possible MH370 impact sites based on discovery of the flaperon on Reunion Island. Scale is +/- 0.035



Comparison of reverse drift and forward-drift likelihood methods

The contrast between the results of the SAROPS reverse-drift estimate for the location of AF447 based on the bodies found 6 to 10 days after the crash and the forward-drift likelihood method for incorporating information from the MH370 flaperon found on Reunion Island more than a year after the loss of MH370 is remarkable. Using reverse drift, the information from the bodies, found only 6 to 10 days after the AF447 crash, provided little helpful information for the location of AF447. By contrast, using the forward-drift likelihood method demonstrated the potential to provide significant information more than a year after the loss.

Moving Search Objects

The discussion so far has centered on the incorporating debris information into the location distribution for a stationary search object. In this section, we describe how to use the forward-drift likelihood method to incorporate debris information into distributions for moving search objects such as missing people or boats in the ocean.

For a moving search object, we begin with the object location distribution at the time of loss. Designate this as time $t = 0$. Search for a moving object requires that one specify a (probabilistic) model for the movement of the search object over time, so that one can forecast the probability distribution for the object location at any time $t > 0$. For the convenience of this discussion, we will divide time into discrete intervals so that $t = n$ refers to the nth time interval, and we will treat the object as stationary during a time interval. (Note, SAROPS uses a continuous-time object motion model.)

To incorporate debris information, one calculates the likelihood function using (2) and (3) above and incorporates it into the object location distribution at $t = 0$ using (4). One then applies the motion model to this distribution to obtain the updated distribution at any time $t > 0$. If there has been unsuccessful search during time interval $t = n$, then one must compute the posterior at $t = n$ given this unsuccessful search before motion updating to times $t > n$. If one is planning a search at time t, then one needs to use the object location distribution at that time updated for the debris information and unsuccessful search. This will yield more effective and efficient search plans.

The process just described requires re-computation of the object location distribution from $t = 0$ to the present accounting for the debris information, unsuccessful search, and object motion. In SAROPS this is not necessary because SAROPS uses the motion model to generate a large number K of possible continuous time sample paths for the object over the time period of interest. Each path gives a possible location for the search object as a function of time. Each path has a weight (probability) assigned to it, usually $1/K$ at time $t = 0$. As the search progresses, the effect of unsuccessful search on each path is represented in a Bayesian fashion by multiplying its weight by the probability of the search failing to detect the object given it followed this path and then renormalizing so the weights sum to 1. To account for debris information, one simply multiplies the weight of each path by the debris likelihood function value in the cell containing that path at time $t = 0$ and then renormalizing. No other re-computation is necessary. One can use the location distribution based on the reweighted paths' positions at any time t in the future as a basis for planning search at time t.

Uncertain Distress or Loss Time

If the time of the distress or loss of the object is uncertain, then the calculation and application of the debris likelihood function in (2)-(4) is still straight-forward but more complicated. In place of the initial distribution on location in (1), we must specify a distribution on the time s and location j of the loss or distress. Let $s = 1,\ldots,S$ be the possible loss times, the prior in (1) becomes

$$\sum_{s=1}^{S}\sum_{j=1}^{J} p\left(j,s\right) = 1. \qquad (7)$$

The debris likelihood function in (2) becomes

$$L\left((y,T)\,|\,(j,s)\right) = \Pr\left\{\text{Debris floated to position } y \text{ in time } T \,|\, \text{ it originated in cell } j \text{ at time } s\right\}. \qquad (8)$$

The posterior distribution on the time and position of loss or distress in (4) becomes

$$\tilde{p}(j,s) = \frac{L\left((y,T)\,|\,(j,s)\right) p(j,s)}{\sum_{s'=1}^{S}\sum_{j'=1}^{J} L\left((y,T)\,|\,(j',s')\right) p(j',s')} \text{ for } j = 1,\ldots,J \text{ and } s = 1,\ldots,S. \qquad (9)$$

Conclusion

This paper has presented a Bayesian forward-drift method of incorporating debris information into a search object location distribution. It compared this method to the reverse-drift method commonly used by SAROPS and other search and rescue planning programs. We showed by example that reverse drift can lead to a distribution with very large uncertainties which does not provide useful information on the object location. By contrast, we presented an example using the Bayesian forward-drift method that showed that even debris recovered more than a year after the loss can provide valuable location information. Finally, we discussed how to extend the forward-drift method to moving search objects and to search objects whose time of distress or loss is uncertain. The forward drift method needs to become the new standard for incorporating information from drifting debris.

About the authors

Lawrence D. Stone. Dr Stone joined Metron in 1986. He became Chief Operating Officer in 1990 and Chief Executive Officer in 2004. In 2010 he returned to primarily technical work as Chief Scientist. He was the major technical contributor to the U. S. Coast Guard's Search and Rescue Optimal Planning System (SAROPS) which went into operation in 2007. He is a co-author of the books, *Bayesian Multiple Target Tracking* and *Optimal Search for Moving Targets*. The Operations Research Society of America awarded the Lanchester Prize to Dr Stone's book, *Theory of Optimal Search*, as the best work in operations research in 1975.

In 1986, Dr Stone used Bayesian search methods to produce the probability maps used by the Columbus America Discovery Group to locate the *S.S. Central America* which sank in 1857, taking an estimated three tons of gold coins and bars to the ocean bottom one and one-half miles below. He headed the Metron team that used Bayesian methods to produce the probability maps that led to the location on April 3, 2011 of the wreckage of the AF447 flight which disappeared over the Atlantic in June of 2009. Recently Dr Stone used Bayesian methods to combine historical, topological, and geophysical information to find the lost (since the end of the 16th century) Spanish gold city of Logroño de los Caballeros in the jungles of Ecuador.

In 1999 Dr. Stone was elected to the National Academy of Engineering. He is a fellow of the Institute for Operations Research and Management Science. In 2008 he was awarded the J. Steinhardt Prize for outstanding contributions to Military Operations Research by the Military Applications Society.

J. Van Gurley. Mr. Gurley joined Metron in 2013 and became President and Chief Executive Officer in 2019. Prior to his current role, Mr. Gurley served as Chief Operating Officer, Senior Vice President, and Senior Manager at Metron where he led a number of rapid innovation projects in predictive analytics, data fusion, and automated mission planning for the Federal Aviation Administration, U.S. Navy, and Defense Advanced Research Projects Agency.

Before joining Metron, Mr. Gurley completed a 26-year career in the United States Navy rising to the rank of Captain while serving as a submarine warfare officer and naval meteorology and oceanography specialist. During his navy career, he led several strategy and innovation efforts that transitioned new technologies into fleet operations. These included development and execution of a complete restructuring of the naval oceanography community's undersea warfare support programs coupled with accelerated fielding of major new technologies in unmanned ocean sensing, ocean and acoustic modeling, and mission planning. While serving as the Military Deputy/Executive Assistant for the Oceanographer of the Navy in the Pentagon, he served on the leadership team that developed the U.S. Navy's first strategy and policy for climate change.

Mr. Gurley has degrees in physics, engineering, and management from the Massachusetts Institute of Technology, Woods Hole Oceanographic Institute, and University of Florida. His research work was honored with the Ruth and Paul Fye award for excellence by the Woods Hole Oceanographic Institute Applied Ocean Physics and Engineering Department. In addition, he was the U.S. Navy's 2003 Federal Executive Fellow with the Massachusetts Institute of Technology Security Studies Program.

John R. Frost. Mr. Frost joined the U.S. Coast Guard in 1971 and retired from active duty with the rank of Commander in 1994. During this time, he served aboard the USCG Cutter Taney, at Rescue Coordination Center, San Juan, PR, the Operations Analysis Branch of USCG Atlantic Area (lead analyst for Computer Assisted Search Planning), obtained an MS in Computer Science from the US Naval Postgraduate School, served as assistant Chief of Search and Rescue for USCG Atlantic Area, Commanding Officer of USCG Operations Computer Center, and Special Projects Officer (SAR) at USCG Research and Development Center. After this he joined Soza & Co., developing portions of the USCG SAR Addendum and portions of the International Aeronautical and Maritime Search and Rescue (IAMSAR) Manual. In 2004 Mr. Frost returned to USCG employment as a civil servant with the Office of Search and Rescue at USCG headquarters in Washington, DC. He is the principal architect of the USCG's Search and Rescue Optimal Planning System (SAROPS) and continues to serve as the Program Manager for SAROPS.

Abbreviations

AF	Air France
ATSB	Air Transport Safety Board
BEA	Bureau of Enquiries and Analyses
DST	Defense Science and Technology

LKP	Last Known Point
MH	Malaysian Airlines
nm	nautical miles
SAROPS	Search and Rescue Optimal Planning System

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