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Improving light and temperature based geolocation by unscented Kalman filtering

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Abstract

Tracking marine animals with electronic tags has become an indispensable tool in understanding biology in relation to movement. Combining light based geolocation estimates with an underlying movement model has proved helpful in reconstructing the most probable track of tagged animals. These tracks can be further improved by including the tag measured sea-surface temperature and matching it to external sea-surface temperature (SST) data. The current methodology for doing this in a state-space model requires that external sea-surface temperature be smoothed before it is used in the model, and further that its gradient field is pre-calculated. This two-step approach has a number of technical drawbacks, and the final statistical inference about the most probable track is consequently less convincing. This paper presents a new methodology (refer to as UKFSST) where all steps, including the SST smoothing, are handled within one coherent model. An additional benefit is that even the degree of smoothing, which was previously pre-determined and fixed, can now be optimally selected. UKFSST offers better handling of non-linearities in Kalman filter, and provides a statistically sound model for geolocation applications, as opposed to *ad hoc* SST matching approaches.

Keywords: Unscented Kalman filter (UKF); Light-based geolocation; Sea-surface temeperature; UKFSST; Archival tag; Pop-up satellite archival tag

1. Introduction

Electronic data storage tags, both archival tags and popup satellite archival tags, are used extensively to study a variety of marine species, from squid to turtles, tunas, billfishes and sharks (Arnold and Dewar, 2001; Gunn and Block, 2001). Information derived from these tags provides valuable new insights into the spatial dynamics (Schaefer and Fuller, 2002; Stokesbury et al., 2004; Bonfil et al., 2005; Sibert et al., 2006), habitat utilization (Horodysky and Graves, 2005; Schaefer et al., 2007), behavioral and physiological ecology (Lutcavage et al., 1999; Block et al., 2001; Weng et al., 2005; Dagorn et al., 2007; Malte et al., 2007), population structure (Block et al., 2005) and fisheries interactions (Graves et al., 2002; Moyes et al., 2006) of these species. Measuring depth (pressure), temperature and light-level data, data storage tags are often deployed on animals that spend most of their time submerged underwater, where satellite telemetry via Global Positioning System or Argos is unavailable. Thus, horizontal position estimates from these tags can only be inferred from the recorded ambient light-level data (i.e. light-based geolocation). Estimated times of dawn and dusk are used to calculate longitude from the time of local noon, and latitude from the local day length (Wilson et al., 1992; Hill, 1994; Ekstrom, 2004). Previous studies on the accuracy of light-based geolocation have established that raw geolocations (i.e. unfiltered and uncorrected estimates), especially for latitude, are often unreliable (Gunn et al., 1994; Welch and Eveson, 1999; Metcalfe, 2001; Musyl et al., 2001). Physical (e.g. days around the equinox, where day length is nearly equal at all latitudes) and biological factors (e.g. diving behavior in swordfish or bigeye tuna) confound the position estimation from light data even further. The magnitude and extent of geolocation errors severely limit the utility of electronic tagging data, and have prompted the development of various improved approaches.

Sibert and Fournier (2001) introduced a state-space statistical model in combination with the Kalman filter to estimate

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a "most probable" track with geolocation errors and parameters relevant to population movement. A widely used approach (Musyl et al., 2003; Sibert et al., 2003; Wilson et al., 2005), this model is freely available as the KFtrack package (Nielsen and Sibert, 2004), a plug-in for the open-source statistical software R. Nielsen et al. (2006) extended this model by incorporating sea-surface temperature data and made it available as the KFSST package (Nielsen and Sibert, 2005). We present here a new method that further refines this state-space model by using the unscented Kalman filter and sea-surface temperature to improve geolocation estimates.

The current model in KFtrack and KFSST (collectively referred to here as KF) assumes that the movement of a tagged animal can be approximated by a biased random walk, and that raw geolocations are representations of the true positions with some measurement errors. Measurement errors are parameterized to produce larger latitude errors during the several days around the equinox, which is often an artifact of light-based geolocation (Hill and Braun, 2001). KFSST combines the raw geolocations with external (e.g. satellite-derived) sea-surface temperature data and uses both types of information in the state-space model. This requires the external sea-surface temperature field to be smoothed and its gradient calculated before entering the model. This two-step approach has a number of technical drawbacks, including the need to decide, a priori, on an appropriate scale of smoothing, which depends on factors like ocean dynamics and cloud cover in the study area (Nielsen et al., 2006). This paper addresses this shortcoming with a new model that eliminates the two-step approach, and handles all observations, including the necessary smoothing of SST data, within a single coherent state-space model. We will refer to this new approach as UKFSST, or simply, UKF.

2. Materials and methods

2.1. Tagging data

Data from eight pop-up satellite archival tags (PSATs) and one satellite telemetry tag from three separate studies were obtained for our analysis. The number of available geolocation observations from these tags varies from 21 to 138 (Table 1). This corresponds to a range of 21–182 days at liberty, since light-based geolocation may fail to generate a position estimate for some days in the tagging period. Six striped marlins, *Tetrapturus audax* (Tag 7, 8, 13, 34, 38 and 46), were fitted with PSAT tags from Wildlife Computers as part of a Pacific-wide study of striped marlin movement. Details of the study and tagging procedures are described in Domeier (2006). Data recovered from these tags were processed with the manufacturer light-based geolocation software that employs the dawn and dusk symmetry method (Hill and Braun, 2001). One blue shark (*Prionace glauca*) was fitted with a PSAT tag from Microwave Telemetry in an investigation to determine post-release survivability. Data from this tag are available as an example dataset in the KFSST package. Tagging procedures are described in Nielsen et al. (2006). In a survey conducted by the Southwest Fisheries Science Center shark research program, one mako shark *Isurus oxyrinchus* (Mako 3), was tagged with a Wildlife Computers PSAT tag and a smart position only (SPOT) tag (D. Holts, unpublished data). Data from the PSAT tag were processed with the manufacturer light-based geolocation software. The SPOT tag is a satellite telemetry tag that communicates with the Argos satellite system for its position estimates. An accuracy flag, referred to as the location class (LC), is associated with each position estimate. Only estimates with known errors (i.e. LC 1, 2 and 3) were selected for our analysis. Errors for LC 1, 2 and 3 are

Table 1
Parameter estimates for all tags analyzed with UKFSST

Tag	obs	$\log L$	u	v	D	b_x	b_y	b_{sst}	σ_x	σ_y	σ_{sst}	a_0	b_0	Radius, r
Open ocean														
1. Marlin Tag 34	108	415.83	8.83	7.20	402.73	0.34	0.26	0	0.09	1.34	0.39	0.006	−13.27	127.16
2. Marlin Tag 38	49	185.08	2.30	−7.14	270.72	−0.06	0.82	0	0.08	1.39	0.20	0.004	−8.28	180.97
3. Blue shark	45	320.25	−7.92	4.56	1229.45	0	−3.22	0	3.21	2.77	0.60	0.125	43.71	719.35
Near coast														
4. Marlin Tag 7	68	290.84	−3.45	−4.47	345.40	0	−1.87	0	0.34	1.56	0.42	0.159	44.65	288.76
5. Marlin Tag 8	21	96.31	−10.48	−23.26	279.27	0.05	1.21	0	0.16	2.35	0.64	1.10e−08	−20.72	358.68
6. Marlin Tag 13	82	401.64	0.82	−14.18	894.69	0	−1.46	0	0.97	2.48	0.28	0.119	16.66	189.40
7. Marlin Tag 46	27	82.65	3.72	4.06	87.73	−0.36	0.37	0	0.43	0.17	0.38	0.015	76.37	92.69
8. Mako 3	138	811.12	0.66	0.53	175.79	0.33	1.50	0	0.47	3.13	1.72	0.025	−10.70	116.49
KFSST error estimates														
a. Blue shark									3.34	2.64	0.48			
b. Marlin Tag 7									0.38	1.58	0.44			
c. Marlin Tag 46									0.58	0.77	0.71			
d. Mako 3									0.50	3.88	1.08			

A value of zero indicates models in which the parameters were not active, and thus not estimated. obs is the number of observations in each track; $\log L$ is the negative log-likelihood value of a model (the smaller the value, the better is the model fit). u and v are expressed in nm day^{-1}; D is in nm^2 day^{-1}; b_x, b_y, σ_x, σ_y, σ_{sst} are in degrees; b_{sst}, σ_{sst} are in Celsius; a_0, b_0 are in days and smoothing radius, r, is in nautical miles. Reynolds Optimally Interpolated SST (RS) was used as the SST field for all runs except Tag 38, where CoastWatch Blended SST (BA) was used. Error estimates from KFSST are also shown for comparative purposes.

1000, 350 and 150 m, respectively. To facilitate comparison with PSAT data, Argos estimates for a given day were averaged to generate a single longitude and latitude estimate ($\overline{\text{loc}}_{\text{Argos}}$).

2.2. Satellite sea-surface temperature (SST) imagery

Three satellite-derived SST products were acquired for inclusion in the UKF model. The NCEP Reynolds Optimally Interpolated SST product is an interpolation of satellite-derived Pathfinder Advanced Very High Resolution Radiometer (AVHRR) and in situ measurements of SST (Reynolds and Smith, 1994). It provides a continuous 1° by 1° globally gridded dataset that eliminates data gaps due to cloud cover. To simplify computations, the 8-day composite (accuracy estimated at 0.5–0.7 °C), was used as the default SST field for running the UKF model. Two finer-scale products were also used to look at the influence of SST spatial resolution on UKF model performance. The NOAA POES AVHRR Global Area Coverage (GAC) 8-day SST composite product is gridded at 0.1° by 0.1° (∼11 km) and has an accuracy of 0.3–0.5 °C (Walton et al., 1998; Vazquez et al., 1998). Lastly, the NOAA CoastWatch Experimental Blended SST is derived from both microwave and infrared sensors carried on multiple platforms (NOAA, 2007a). The advantage of including microwave sensors is that they can acquire measurements in the presence of clouds, although their coarser spatial resolution may be considered inadequate for coastal applications. This shortcoming is addressed by supplementing with SST measurements collected via multiple infrared (IR) platforms. Resulting 5-day composite data of 0.1° by 0.1° resolution (accuracy unknown) were obtained through the publicly available NOAA BloomWatch 360 website (NOAA, 2007b).

2.3. Model description

The UKF model is very similar to the KF model described in Nielsen et al. (2006), and will only be briefly described here with focus on the differences. The model is a state-space model, where the transition equation is describing the movements. A random walk model is assumed:

$$\alpha_i = \alpha_{i-1} + c_i + \eta_i, \quad i = 1, \ldots, T \tag{1}$$

Here α_i is a two-dimensional vector containing the coordinates $(\alpha_{i,1}, \alpha_{i,2})$ in nautical miles along the sphere from a translated origin at time t_i, c_i is the drift vector describing the deterministic part of the movement, η_i is the noise vector describing the random part of the movement and T is the number of observations in the track. The deterministic part of the movement is assumed to be proportional to time $c_i = (u\,\Delta t_i, v\,\Delta t_i)'$. The random part is assumed to be uncorrelated and follow a two-dimensional Gaussian distribution with mean vector 0 and covariance matrix $Q_i = 2D\,\Delta t_i I_{2\times 2}$. Here D is a model parameter quantifying the diffusive movement component and $I_{2\times 2}$ is the two-dimensional identity matrix. The measurement equation is a non-linear function describing the expected observation at a given state (α_i). Each observation y_i consists of three elements: longitude, latitude and SST. The first two coordinates are the raw light-based geolocation estimates and the last is the SST recorded by the tag. The measurement equation describing y_i is:

$$y_i = z(\alpha_i) + d_i + \varepsilon_i, \quad i = 1, \ldots, T \tag{2}$$

The first two coordinates of z comprise the coordinate change function, and the last coordinate describes the expected SST at a given position. z is given by:

$$z(\alpha_i) = \begin{pmatrix} \dfrac{\alpha_{i,1}}{60\cos(\alpha_{i,2}\pi/180/60)} \\ \dfrac{\alpha_{i,2}}{60} \\ \tau_r\left(\dfrac{\alpha_{i,1}}{60\cos(\alpha_{i,2}\pi/180/60)}, \quad \dfrac{\alpha_{i,2}}{60}\right) \end{pmatrix} \tag{3}$$

Here the factor $\pi/180$ converts from degrees to radians and 60 is the distance corresponding to 1° of longitude at the equator. The function τ_r (longitude, latitude) describes the expected SST at a given location and time. The function τ_r predicts the SST by a weighted average of SST observations from satellite within a radius of r nautical miles. The inner workings of τ_r is the subject of the next section.

The observational bias $d_i = (b_{\text{lon}}, b_{\text{lat}}, b_{\text{sst}})'$, describes systematic measurement errors, for instance, if the internal clock in the tag is not absolutely correct. The measurement error ε_i is assumed to follow a Gaussian distribution with mean vector 0 and covariance matrix H_i. Longitude and SST variance are assumed constant, but the latitude variance increases near equinoxes (see Nielsen et al., 2006, for details).

2.4. Data structure: Quadmap

A Quadmap is a data structure that allows quick access all points near any given position (x, y) in an axis-parallel plane (Finkel and Bentley, 1974). The time to lookup the objects at or near a given point is $O(\max\{\log N, R\})$ where N is the total number of objects and R is the number or objects returned by the query. This quick access to neighboring points is essential to this model, as each likelihood evaluation can require hundreds, or even thousands of these queries, and the number of points N in the satellite SST data can be hundreds of thousands. Intuitively, a Quadmap can be considered a two-dimensional equivalent of a binary search. The neighboring points are identified by recursively subdividing the initial rectangle into four sub-rectangles, and then only searching in the relevant rectangles.

2.5. Unscented Kalman filter

The basic Kalman filter (Harvey, 1990) assumes that both the transition equation and the measurement equation of the state space model are linear. The extended Kalman filter (Harvey, 1990) can handle slight non-linearities by local first order Taylor approximations of the non-linear functions in the model. The unscented Kalman filter (Julier et al., 2000) is a more recent sequential estimation technique. It is very similar to the extended Kalman filter, but instead of approximating the non-linear functions, the transformed probability distributions are approximated directly. This is done by representing the distribution by a set of cleverly selected points, transforming these points by the non-linear function, and then approximating the mean and variance of the transformed distribution, by the mean and variance of the transformed points. This approach gives a simpler implementation, not requiring derivatives of the equations in the state space model, and higher accuracy—at least corresponding to a second order Taylor approximation (Julier et al., 2000).

2.6. Comparison to Argos positions

To compare the accuracy of longitude and latitude estimates from the UKF and KF models, the root-mean-square (RMS) error between the model estimates and Argos positions was calculated. In accordance with Teo et al. (2004):

$$\text{RMS error} = \sqrt{\frac{\sum(\overline{\text{loc}}_{\text{Argos}} - \text{loc}_{\text{estimated}})^2}{n-1}} \quad (4)$$

where loc is either longitude or latitude and n is the number of samples.

2.7. Comparison to EASy FishTracker

The UKF model was compared with EASy FishTracker, a different geolocation estimation algorithm developed by Domeier et al. (2005). Similar to previous sea-surface temperature (SST) matching approaches (Teo et al., 2004), EASy FishTracker (EASy) employs a non-statistical approach to indirectly estimate position by matching tag and satellite SST data within a local neighborhood. It allows latitudinal positions to be estimated by only using two observation types, longitude and SST. Manufacturer latitude estimates are not necessary, but can be included where appropriate. In this particular analysis, for a given manufacturer longitude estimate, a SST-search neighborhood was set to be 60 nautical miles (1° longitude) from eastward and westward of the longitude estimate, and movement speed was constrained not to exceed four knots (kn, 1 knot = $\sim 0.5144\,\text{m}\,\text{s}^{-1}$). While SST imagery is not smoothed, at any point before or within the model, temporal composites are constructed and used. For a detailed description of the EASy model, refer to Domeier et al. (2005) and Tsontos et al. (2006). Data from two tags (Tag 34, 38) were analyzed with both models using the NOAA CoastWatch Blended SST product (BA) to evaluate their performance.

3. Results

3.1. UKF model performance

UKF is a broader and more general model, where the KF model is in fact a special case of it. As expected, results from

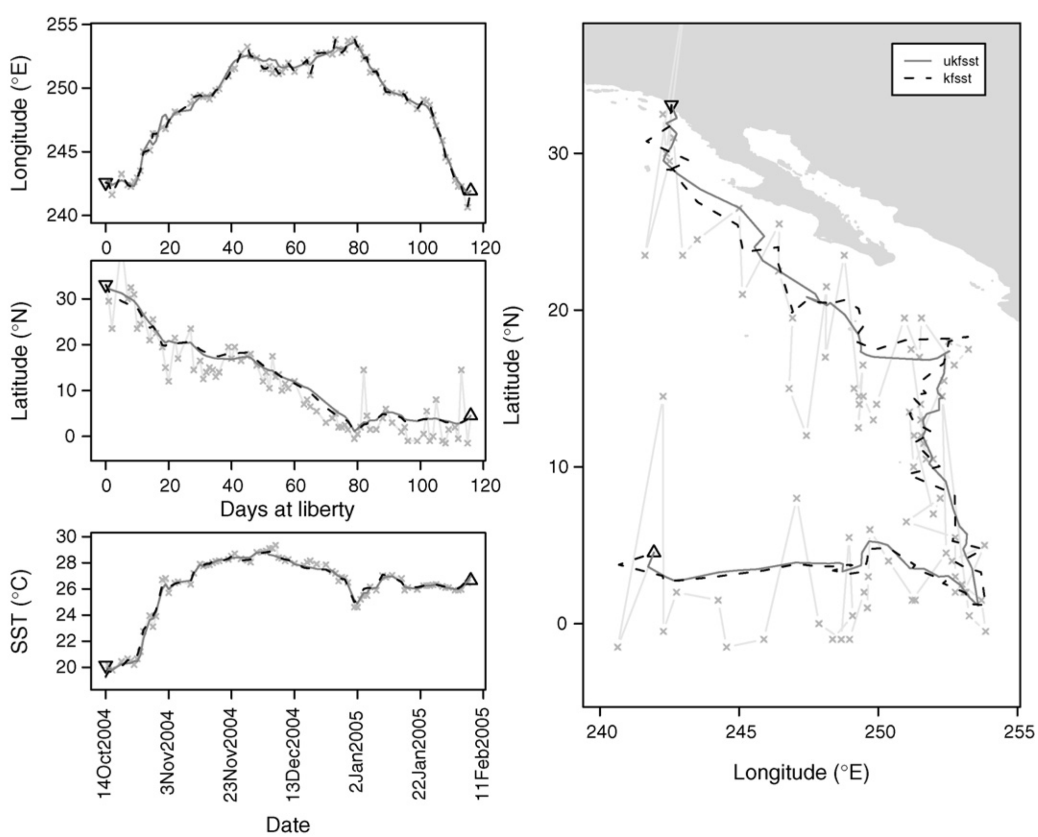

Fig. 1. Most probable tracks for a marlin, Tag 13, fitted by UKF (solid line) and KF (dashed line). The thin line connects the raw light-based geolocations. The left panel shows how well the models fit the three different data types (longitude, latitude and SST) and are plotted on a common temporal axis scale. Raw geolocations and observed SST are marked by crosses; the deployment point is indicated with an open inverse triangle (▽) and the known pop-up position is given by an open triangle (△).

running both models with the same set of tag data and model parameters (except the addition of radius (r) as a model parameter in UKF) are similar. Differences in estimates between the two models are minimal for all three available types of observations: longitude, latitude and SST (Fig. 1). Both models are able to estimate a "most probable" track that is more reliable than that of the manufacturer geolocation.

Cases in both the open ocean and near the coast were also evaluated. The models delivered very similar performance in all cases (Fig. 2). Most of the longitude or latitude estimates from the two models fall either on top of or right next to each other. With only a few exceptions, the estimates from KF are within the confidence interval of the UKF model. Error estimates in longitude, latitude and SST (σ_x, σ_y, $\sigma_{\rm sst}$) are similar between the two models (Table 1), and often UKF obtains lower error in position estimates (σ_x, σ_y).

Table 1 summarizes the parameter estimates from UKF for all eight tags analyzed in this paper. The diffusion estimate (D) spans a wide range from 88 to 1229 nm^2 day^{-1}, reflecting the fact that different species and individuals were analyzed. Errors in longitude (σ_x) and latitudes (σ_y) estimates, in most cases, are less than 0.5° and 3°, respectively. The smoothing radius (r) varies from 90 to 700 nautical miles. General geographical location, whether in the open ocean or near the coast, does not seem to influence the extent of the smoothing radius.

3.2. Comparison to Argos positions

The double-tagged mako shark has provided a valuable reference dataset with which to compare the accuracy of the two models. As evident from the Argos longitude and latitude estimates (Fig. 3, solid line), the tagged shark exhibited two distinct movement modes: migratory (day 0–90), and localized movements (day 90 onwards). Both models generate accurate longitude estimates (RMS error = 0.5° for UKF; 0.5° for KF, $n = 86$) when compared to the Argos estimates. They also capture the period with more restrained longitude estimates as the shark became more localized around day 90. The model esti-

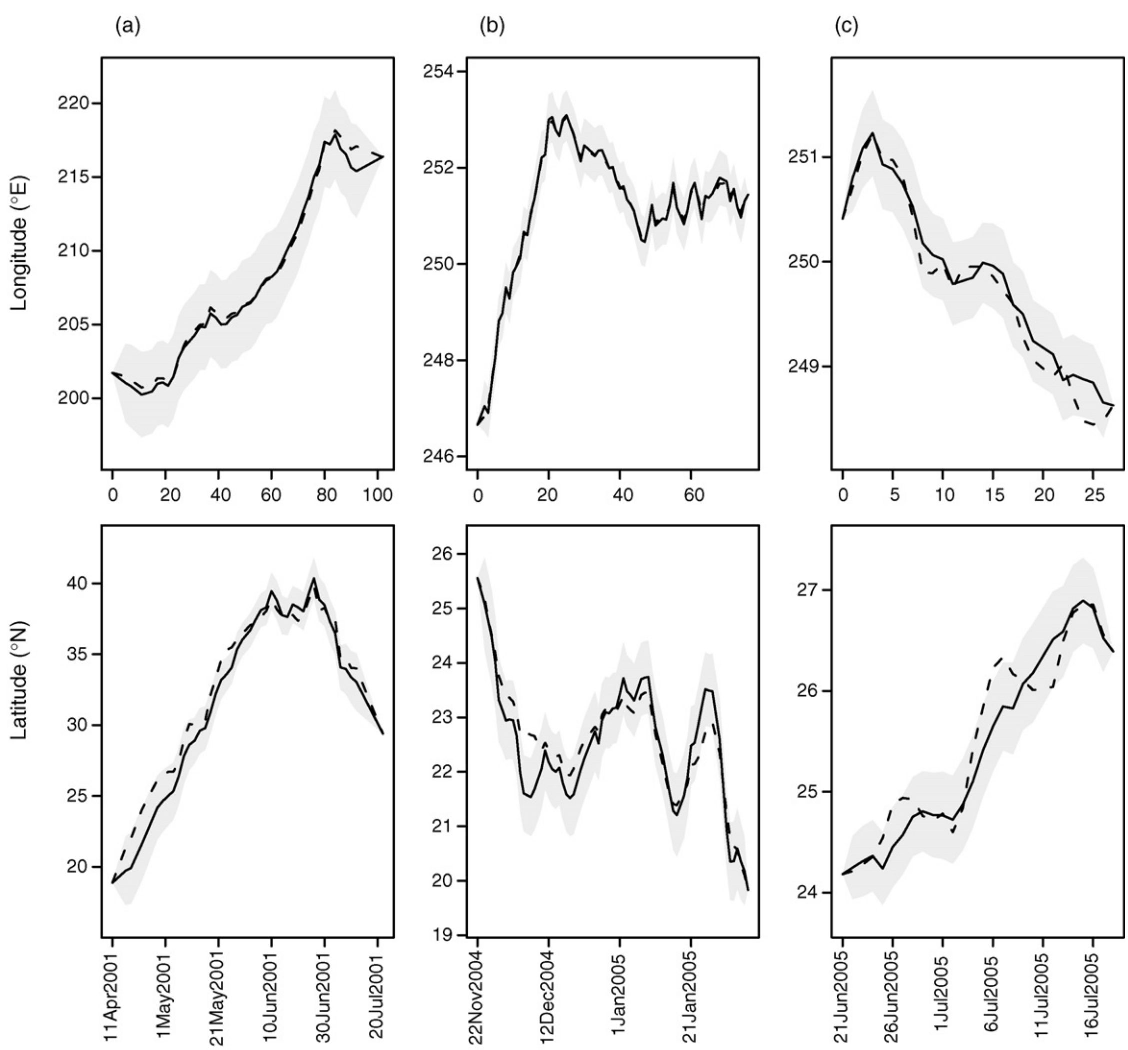

Fig. 2. Most probable track estimates for longitude and latitude over time for a blue shark (a) and two marlins, Tag 7 (b) and Tag 46 (c), fitted by UKF (solid line) and KF (dotted line). The shaded region indicates the 95% confidence interval estimated by UKF. Raw light-based geolocations are not shown here for clarity.

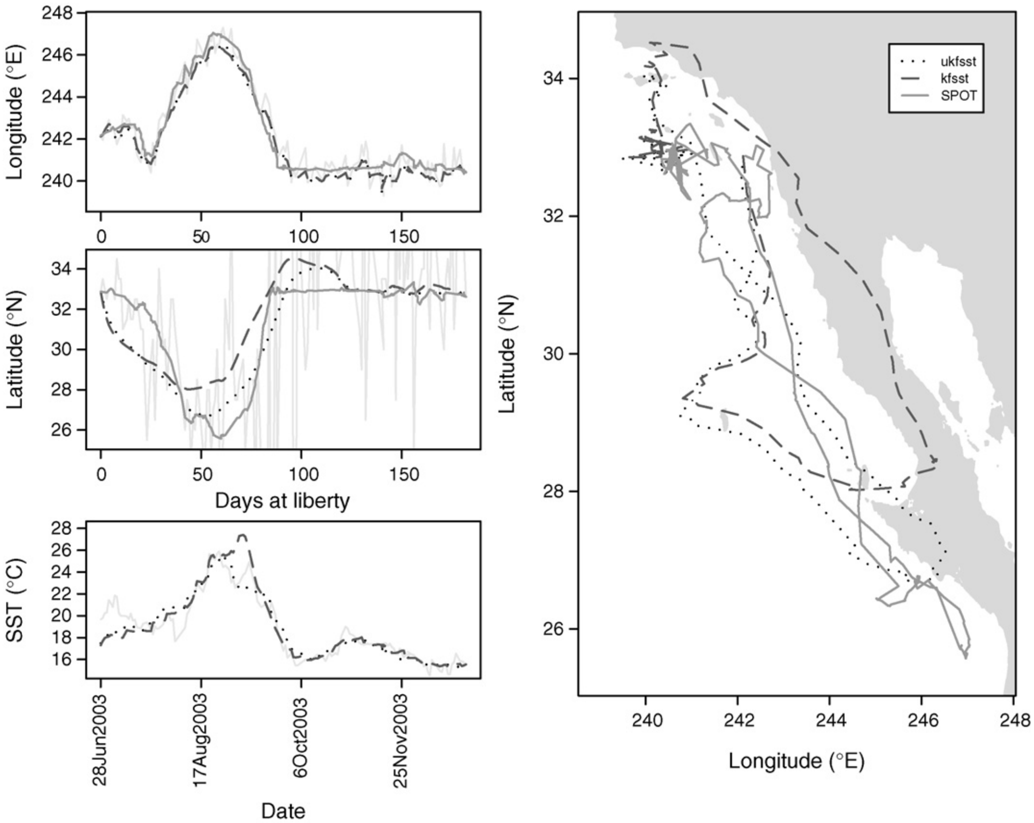

Fig. 3. Most probable tracks for a mako shark, Mako 3, fitted by UKF (dotted line) and KF (dashed line). Mako 3 was also double-tagged with a SPOT tag that provided positions from the Argos system (solid line). The left panel shows how well the models fit the three different information sources (longitude vs. days at liberty, latitude vs. days at liberty and SST vs. date). Raw light-based geolocations and observed SST are outlined with thin lines. Note that the SPOT tag did not record any temperature data.

mates fluctuate more than the Argos estimates between days 90 and 140 when the Argos longitudes were very much fixed at 241°E. For latitude estimates, the overall shape of all estimates is similar for both models (RMS error = 1.2° for UKF; 1.8° for KF, $n = 86$). UKF estimates are located more southwards between days 40 and 100, and track the Argos values more closely than KF estimates. However, both models lag behind in switching to a more constant latitude when the Argos latitude remained at 31°E since day 85, and then eventually manage to track back the Argos estimates around 120 days. This discrepancy is likely due to the fact that manufacturer light-based geolocation estimates had huge latitude errors (up to 30°), making the measurements less useful for the model. Both models were able to match up with SST observations measured by the tag very closely, except at the very beginning when the shark first swam along the coast during the first 10 days at liberty.

3.3. SST resolution

The effect of differing SST imagery resolution on the model performance was investigated for an open ocean case and a coastal case. Table 2 summarizes the UKF model parameters for

Table 2
Parameter estimates for two tags fitted by UKF using three different satellite imagery sources

Tag	Imagery	obs	log L	u	v	D	b_x	b_y	b_{sst}	σ_x	σ_y	σ_{sst}	a_0	b_0	Radius, r
Open ocean															
1. Marlin Tag 34	RS	108	415.83	8.83	7.20	402.73	0.34	0.26	0	0.09	1.34	0.39	5.74e−03	−13.27	127.16
	AG	108	397.13	8.49	7.37	380.04	0	−0.02	0	0.09	1.26	0.34	4.47e−03	−11.82	114.36
	BA	108	382.67	10.37	6.54	323.95	0.44	0.15	0	0.23	1.20	0.22	4.74e−03	−12.91	43.45
Near coast															
2. Marlin Tag 8	RS	21	96.31	−10.48	−23.26	279.27	0.05	1.21	0	0.16	2.35	0.64	1.10e−08	−20.72	358.68
	AG	21	96.40	−12.44	−19.22	484.51	0	3.07	0	0.25	2.38	0.30	1.41e−08	−21.54	37.46
	BA	21	99.29	−11.61	−21.33	287.04	0	0	0	0.32	4.89	0.24	4.87e−07	73.07	26.18

RS denotes Reynolds Optimally Interpolated SST; BA denotes CoastWatch Blended SST; AG denotes AVHRR-Global Area Coverage 8-day. A value of zero indicates models in which the parameters were not active, and thus not estimated. A value of zero indicates models in which the parameters were not active, and thus not estimated. obs is the number of observations in each track; log L is the negative log-likelihood value of a model. u and v are expressed in nm day^{-1}; D in nm^2 day^{-1}; b_x, b_y, σ_x, σ_y, σ_{sst} in degrees; b_{sst}, σ_{sst} in Celsius; a_0, b_0 in days and smoothing radius, r, in nautical miles.

each of the two cases using the coarser-scale product, Reynolds Optimally Interpolated SST (RS), and the finer-scale products, AVHRR-Global Area Coverage 8-day (AG) and CoastWatch Blended SST (BA). Finer-scale products yield similar (Tag 8, $\log L \sim -96$) or higher log-likelihood values (Tag 34, $\log L \sim -390$) than the coarser-scale product (Tag 8, $\log L \sim -96$; Tag 34, $\log L \sim -415$). Most parameter estimates are similar across all model runs. The longitude error (σ_x) remains low, and is an order of magnitude lower than the latitude error (σ_y). The smoothing radius (r) varies substantially among models using different SST products, decreasing with the higher spatial resolution SST products.

Satellite SST data spatial resolution does not seem to affect model performance and position estimates for the open ocean. All model runs generate most probable tracks that are positioned next to each other, and match closely to each other across all observations (Fig. 4). For the near coast case, there are only 21 position estimates from light-based geolocation, resulting in a shorter and more difficult track to estimate (Fig. 5). All three runs produce very comparable longitude estimates, while latitude estimates separate out into two groups according to the SST resolution. Latitude estimates from the finer-scale products (AG, BA) are placed more southwards than those of the coarser-scale product (RS). At the same time, finer-scale products (particularly, BA) are able to trace the fluctuations in SST observations more closely than the coarser-scale product (RS). Plotted on a map (Fig. 5), finer-scale product tracks stay away from land for the most of the time, giving more plausible estimates, while the track based on coarser-scale imagery is displaced over land. This displacement is likely an artifact of a much larger smoothing radius for the coarser-scale product (358 nautical miles versus ~30 nautical miles), where over-smoothing allows the association of SST data with positions over land.

3.4. Comparison to EASy FishTracker

Parameter estimates from UKF for Tag 38 and Tag 34 are reported in Tables 1 and 2, respectively (Imagery type, BA). EASy returns a different set of parameters that could not be directly compared to UKF. To allow comparison, position estimates and reconstructed tracks from EASy were plotted along with UKF estimates. Reconstructed tracks from both models are very similar to each other (Figs. 4 and 6). Estimates from EASy are comparable to those of UKF for Tag 34 (Fig. 4) with respect to all observation types. A closer look at Tag 38 (Fig. 6) allows us to differentiate the two approaches. EASy relies on matching tag temperature observations with external sea-surface temperature data, and this is reflected in its estimates tracking closely to most SST observations. Instead of assuming manufacturer longitude estimates are without errors, EASy allows a

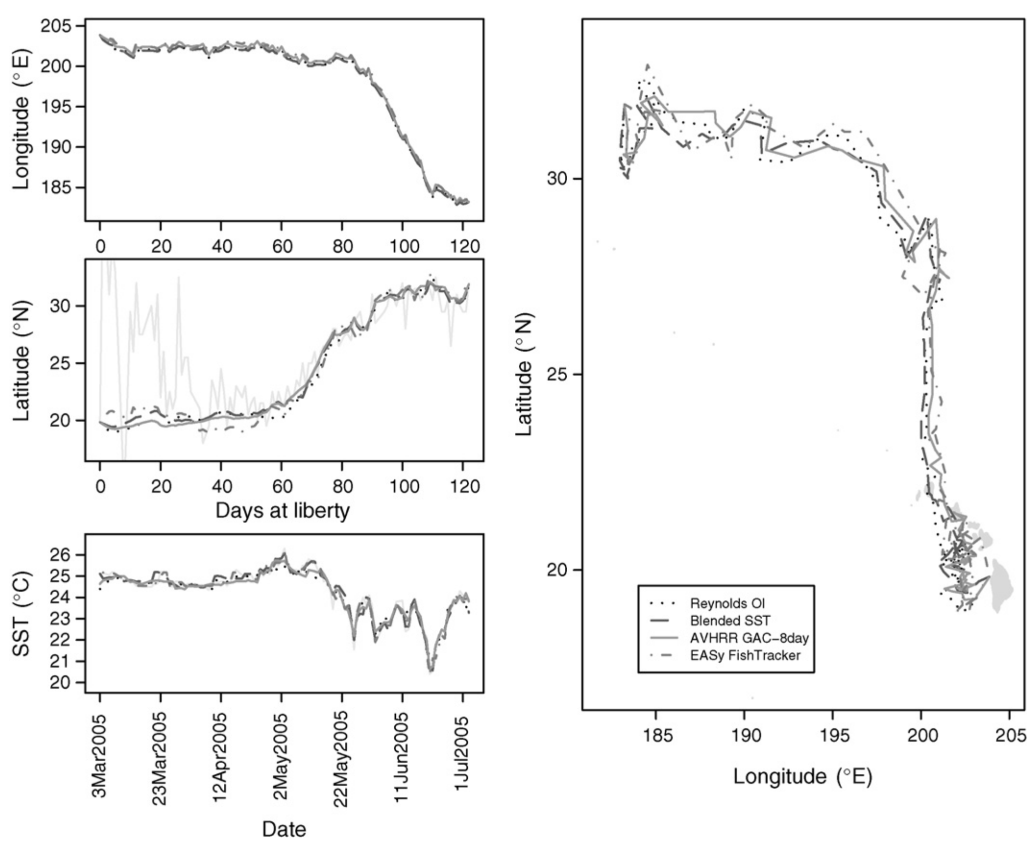

Fig. 4. Most probable tracks for a marlin, Tag 34, fitted by UKF using three different satellite imagery sources: Reynolds OI SST or RS (dotted line); blended SST or BA (dashed line); AVHRR-GAC 8-day or AG (light solid line). A track estimated by the EASy FishTracker algorithm is also plotted (dot–dash line). The left panel shows how well the models fit the three different information sources (longitude vs. days at liberty, latitude vs. days at liberty and SST vs. date). Raw light-based geolocations and observed SST are outlined with thin lines.

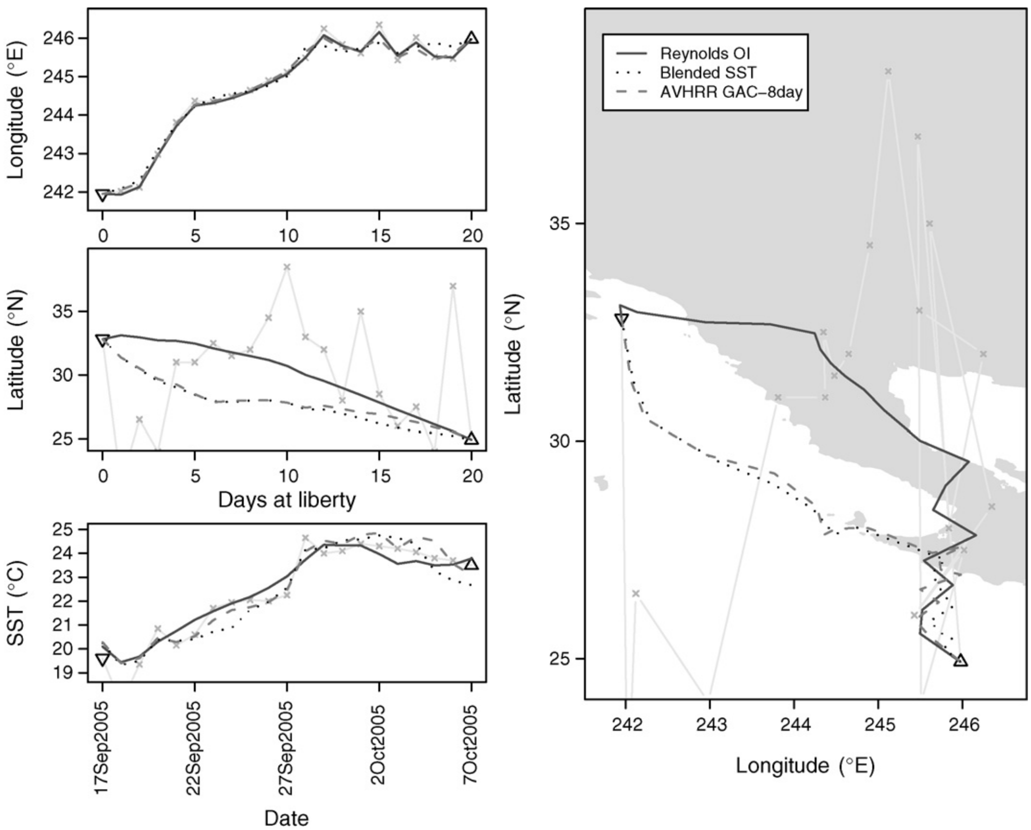

Fig. 5. Most probable tracks for a marlin, Tag 8, fitted by UKF using three different satellite imagery sources: Reynolds OI SST or RS (solid line); blended SST or BA (dotted line); AVHRR-GAC 8-day or AG (dashed line). The thin line connects the raw light-based geolocations. The left panel shows how well the models fit the three different information sources (longitude vs. days at liberty, latitude vs. days at liberty and SST vs. date). Raw geolocations and observed SST are marked by crosses; the deployment point is indicated with an open inverse triangle (▽) and the known pop-up position is given by an open triangle (△).

user-specified search neighborhood (here 60 nautical miles or $\sim 1^{\circ}$) on the either side of a longitude estimate. Consequently, longitude estimates from EASy deviate more from the observations than UKF. In contrast, UKF deals with errors within the state-space model for all observation types and allows the representation of confidence intervals.

4. Discussion

The state-space Kalman filter approach (Sibert et al., 2003) has been shown to improve light-based geolocation estimates for electronic data storage tags and provide movement parameters applicable to population-level models. Our latest extension of this approach utilizes the unscented Kalman filter for estimation and sea-surface temperature as an additional data input.

Comparison with the KF shows that this new extension delivers very closely comparable estimates of the “most probable” track. This is very encouraging as both KF and UKF produce consistent results and ensure compatibility between older results obtained by KF and those of the latest model. It also serves to answer a key criticism of KF on the issue of handling non-linearities. The similarities allow us to conclude that the KF model is robust, and that non-linearities are unlikely to have plagued the model. UKF represents a new coherent model where the smoothing of the SST field is included within the model. Implementation of the UKF model is also streamlined and simplified for the end-user, which allows flexible handling of missing observations and outliers, and utilizes a more efficient SST data look up algorithm.

The UKF model presented in this paper can be extended in many ways. One natural development is to expand beyond sea-surface temperature and utilize tag temperature measured at depths. The amount of smoothing for the temperature at depth field can be estimated by the model as an additional parameter, similar to what is done at the surface. Apart from temperature, other environmental information, such as tides (Hunter et al., 2003; Gröger et al., 2007; Ådlandsvik et al., 2007), bathymetry and salinity (Andersen et al., 2007), may also be included. UKF parameter estimates of movement (u, v and D) are directly comparable to estimated movement parameters from population-scale models estimated via conventional tagging programs. Potentially, the two sets of estimates can even be combined to strengthen confidence in both approaches, and to get a more precise combined estimates (Sibert and Fournier, 2001). Other applications of these parameters include inferring behavior and distribution of tagged fish from multiple tracks (Sibert et al., 2006), and serving as potential inputs for stock assessment models (e.g. MULTIFAN-CL and CASAL).

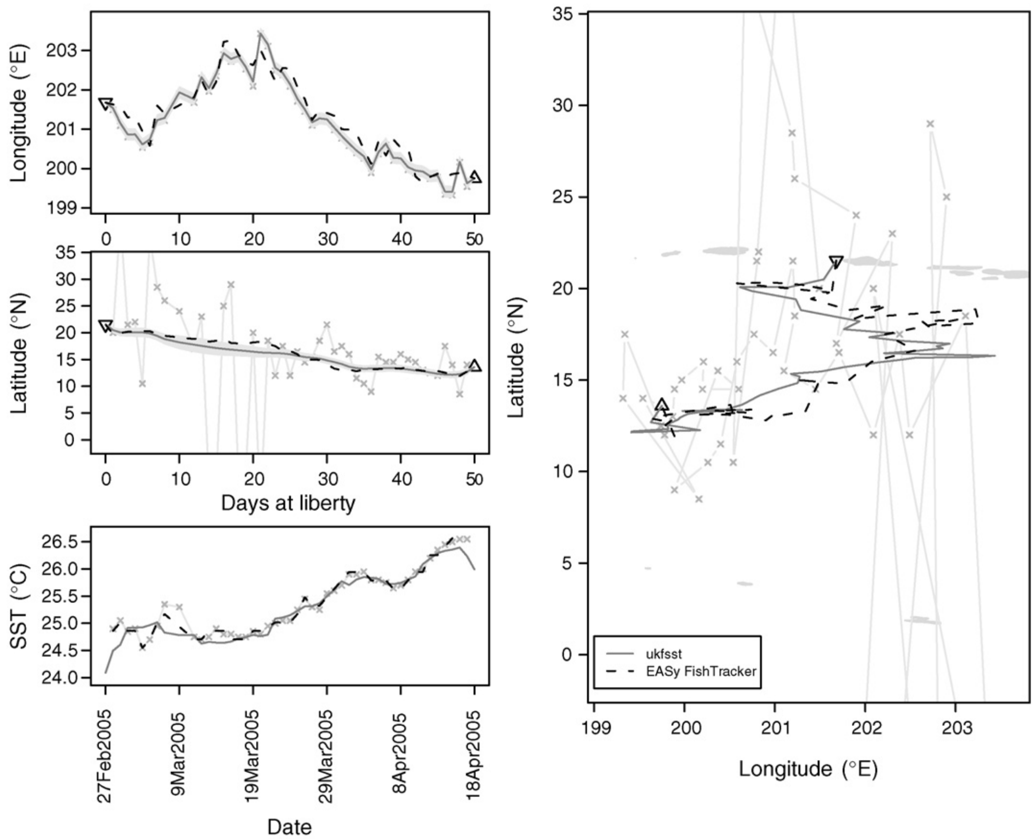

Fig. 6. Tracks estimated by the UKF model (solid line) and the EASy FishTracker (dashed line) algorithm for a marlin, Tag 38. The thin line connects the raw light-based geolocations. The left panel shows how well the models fit the three different information sources (longitude vs. days at liberty, latitude vs. days at liberty and SST vs. date). The shaded region indicates the 95% confidence interval estimated with UKF. Note EASy FishTracker does not generate confidence interval for its estimates. Raw light-based geolocations and observed SST are marked by crosses; the deployment point is marked by an open inverse triangle (▽) and the known pop-up position is marked by an open triangle (△).

4.1. Sea-surface temperature field and smoothing

By assuming longitude estimates are accurate, Smith and Goodman (1986) first demonstrated that in the presence of adequate thermal gradients, sea-surface temperature (SST) matching can improve latitude errors to within 2°. Since then, many studies (e.g. Teo et al., 2004) have successfully applied this approach using a variety of satellite SST products or implementations of the Oceanic General Circulation Model (e.g. Royer et al., 2005). Researchers are challenged by two major questions when employing this approach: (1) which specific imagery products are most appropriate and (2) how to deal with gaps in data due to quality issues. Presently, multiple well-known platforms (e.g. Moderate Resolution Imaging Spectroradiometer, MODIS; Advanced Very High Resolution Radiometer, AVHRR) provide global and regional SST products, which can differ substantially from sensor accuracy and calibration to data processing, quality control and resolution. These product-dependent differences can affect the latitude estimates in a manner that is hard to quantify in the absence of reference track data from GPS or Argos. Non-statistical models with methodologies reliant on sea-surface temperature matching will be more sensitive to the detailed SST product specifications and qualitative aspects of the imagery. Moreover, fine-scale satellite SST products frequently have data gaps caused by the ambient sensor environment (e.g. glares, cloud cover). Common remedies include constructing temporal composites, or designing a spatial smoothing procedure.

State-space models like UKF provide a way to assimilate useful SST information as one of several potential data types, and allow measurement error estimation as part of the model. This is a consistent approach where all observations along with their errors are considered by the model, and no prior assumptions on longitude, latitude estimates and SST product accuracy is made. By estimating the amount of smoothing required for a particular SST field within the model, UKF completely eliminates the arbitrary decisions of SST smoothing and allows tailoring to the regional oceanographic conditions to determine the necessary amount of smoothing. This is a feature consistent with the state-space Kalman filter approach that tag observations and the external data fields are matched locally. The resemblance of the "most probable" tracks using SST products of different resolutions shows that UKF is usually less sensitive to product variations. In cases where the UKF model becomes more sensitive to SST resolution, the smoothing radius (r) serves as a diagnostic parameter. A quick comparison between r and the spatial resolution of the SST product can identify whether the amount of smoothing was inappropriate. Two alternative options are immediately available: first, by using higher spatial resolution products; second, fixing r at a particular value. The latter option excludes the smoothing radius from the model estimation, and no longer allows r to be optimized, which is similar to pre-defining a degree of smoothing in KFSST. Given that UKF is a better model for handling non-linearities, it is beneficial to apply UKF to estimate the other model parameters even when r is not included in the model.

4.2. Comparison to other methodologies and future work

Approaches to improve light-based geolocation almost take the path of convergent evolution. Our initial attempt to compare the UKF model with a matching sea-surface temperature algorithm, EASy FishTracker shows that two very different approaches can generate similar results. Despite this apparent similarity, it must be stressed that a state-space model like UKF considers the measurement errors fully within a statistical framework, and no assumptions regarding the light-based geolocation are made. Nevertheless, it is encouraging that different methodologies arrive at similar solutions, reinforcing our confidence in both approaches. This ensures a wide range of options for researchers to decide upon the best methodology to employ for their particular study.

Future work should seek to extend such a comparison to other improvement algorithms using more examples, preferably with data from double-tagged animals. This calls for greater collaborative effort in sharing tag data, and defining specifications for the usage of tag data and auxiliary environmental information. A full consideration of the regional oceanographic features (e.g. eddies and fronts), and more objective ways to determine the accuracy of position estimates among different methodologies beyond the basic measures like the root-mean square error are also required. This effort to compare various methodologies and establish standards is a prerequisite for the transfer of results between studies using different geolocation estimation procedures, and the inclusion of robust information from tagging studies in resource management applications.

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