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Track Detection of Low Observable Targets Using a Motion Model

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ABSTRACT A method for detecting a low observable target track using an acceleration-based overall motion model is proposed. Unlike the existing track-before-detect methods that are based on sequential state updates, this method computes integrated echo energy for the entire hypothesized motion. The detection and the estimation of the track are made simultaneously using the batch processing approach. A comparison of track detection probability shows higher performance against low observable targets. Using a motion similarity metric and motion model homogeneity, a performance prediction model is derived and compared with the simulation results.

INDEX TERMS Tracking, track before detect, detection, batch processing, hidden Markov model, motion model, weak target, low observable target, marine vehicle.

I. INTRODUCTION

Signal processing can be thought of as the function between the sensor and the decision-making process. In many signal processing applications, including tracking, different levels of trade-offs are made between computational efficiency and decision performance. Limited computational resources stresses the importance of efficiency, which is achieved by making decisions early in the processing chain. However, as the cost of computation decreases, there is more room for the signal processing to retain more sensor data before proceeding to the decision step. In this paper, this will be illustrated in the context of tracking application.

Conventional active sonar tracking is done by thresholding the matched filtered sensor data to estimate the target position, repeated for each transmission. Track of a target is the connection of the position estimates across transmissions [1]. Thresholding, or detection, is an irreversible process through which information is lost, but it allows for efficient information processing afterwards since the following processes only need to work with position estimates and how to connect them, without the need to retain all of the sensor data [2].

One of the shortcomings of the conventional tracking method is that when target echo level is low, also referred to as low-observable target, the thresholding process does not sufficiently separate target energy and energy from non-targets, also known as clutter. As a consequence, higher probability of detection cannot achieved without having to tolerate increase in probability of false detection. Thresholding becomes an unreliable signal processing method for low-observable targets.

Track-before-detect (TBD) approaches were devised to improve reliability of tracking performance by retaining the sensor data longer and making a number of assumptions on viable motion of the target for short period of time. For example, by assuming the maximum speed is known [2]–[4], one can hypothesize a number of potential tracks and compute scores for each hypothesized tracks by applying the data to find the track with the highest score. This approach was theorized and demonstrated by a number of papers including [2] and [5]–[10]. A survey of different TBD approaches were shown in [1].

By making assumptions for motion characteristics, TBD approaches can limit the search space for viable tracks and make decisions within the viable track space making it computationally feasible. TBD approaches are explicitly or implicitly embedding information in the signal processing, thereby assisting the decision and improving the performance. In contrast, when the assumptions are incorrect, these approaches may even perform worse than conventional tracking. For example, if a minimum speed was assumed to be higher than the typical target speed, then the track search space would not include the true track and not even hypothesize anything similar to it, eventually failing to find the true track.

This paper is an extension of the TBD approaches that allows it to perform reliably for low-observable targets at lower signal to noise ratio (SNR) while still maintaining computational feasibility. It is similar to existing TBD approaches in that it makes assumptions about the target motion, and hypothesizes many trial tracks, computes scores or likelihood that indicate how well it is supported by data, then makes the decision toward to the highest-scoring hypothesis. The differences are that it makes the assumption on the motion for longer time scales using a acceleration-based motion model and it employs a notion of motion similarity. Details will be discussed in the following sections.

II. PROBLEM DEFINITION

Consider a set of time series recorded by an acoustic sensor following active transmissions. One of time series is denoted as a scan. Each scan may be matched filtered with the transmitted signal or with the Doppler-compensated matched filter kernel if the radial velocity of the target is assumed. In this section, the matched filtered and basebanded time series data will be the common input to each of the tracking algorithms being compared. Measurement model and target motion model are described in the following sections.

A. MEASUREMENT MODEL

The measurement at each scan, k, is the recorded acoustic time series data denoted as $y_k(t)$, where the argument t is the time since transmission. The matched filtered and basebanded output of each scan, $z_k(t)$, can be expressed as the sum of basebanded autocorrelation function, $R_k(t)$ and the filtered noise, $v_k(t)$.

$$z_k(t) = R_k(t) + v_k(t) \tag{1}$$

One of the properties of the basebanded autocorrelation function, correlation width, w_c, is defined as the $3dB$ width of $R(t)$. This width is known to be inversely proportional to the time-bandwidth product of the transmitted waveform [11]. This quantity will be used to further analyze the target motion in section III-B.

B. TARGET MOTION MODEL

Target motion model is the probabilistic description of the overall motion of the target over the time span of the collected data, *i.e.,* all of the scans. For marine vehicles, one can assume the probability of traveling along a straight path is higher compared to the probability of making frequent abrupt turns, for a given amount observation time. The motion model presented in this paper reflects this assumption, for example, by assigning higher probability to the simple straight motion than the complex multi-turn motion. This is similar to the assumptions made in motion models considered in, for example, [1]–[3]. However, this paper focuses not only on the local curvature, but also on the overall motion over longer time scales, e.g., the number of turns and the time intervals between the turns are also considered in the motion model.

First-order Markov process has been used to describe the position and velocity transitions for the target state dynamics [12]–[14], as well as hidden Markov models (HMM) [15], [16]. These models are expansive in that they allow a search of possible paths close to an exhaustive one, but they are also computationally expensive to perform when the time scale is extended for reliable detection of low-observable targets.

An observation made on marine vehicles is that they exhibit smooth motion due to infrequent and small accelerations. The motion model used in this paper considers the radial acceleration of the target as the hidden state and uses exponential distributions with varying parameter values for each state. As a result, the overall smoothness of the sampled motion is closer to that of marine vehicle's than what is seen from, for example, a first-order Markov process model. Initial position, velocity, and radial acceleration are randomly sampled, and the track over the observation time is determined with Newtonian dynamics using the acceleration sampled from the proposed HMM motion model. 2 shows the equation for target motion expressed in terms of the hidden state, acceleration.

$$a = \frac{dv}{dt} = \frac{d^2r}{dt^2} \tag{2}$$

This motion model is similar to Singer's acceleration-based dynamic model [17], which was applied in tracking applications including [4], [18], and [19] and included in surveys of dynamic models for tracking [20], [21]. While Singer's model uses a combination of uniform distribution and specified probability masses, P_0 and P_{max}, for no acceleration and maximum acceleration, respectively, the motion model used in this paper assumes a symmetric exponential distribution for the magnitude of the acceleration centered at no acceleration as shown in Figure 1.

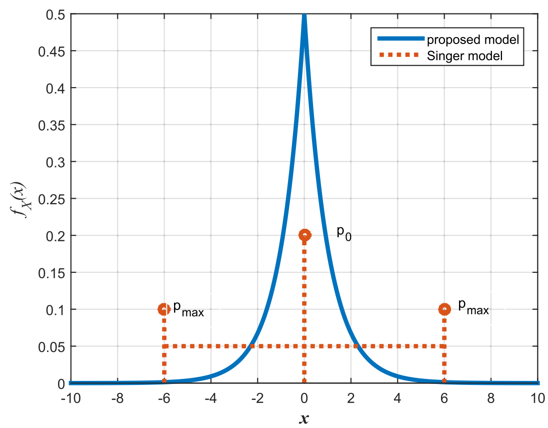

FIGURE 1. PDFs of acceleration, Singer's model and the proposed model.

C. TRACK DETECTION

As seen in Figure 2, the position of the target changes from one scan to the next. The time-varying position of the target over multiple scans is defined as the track, $\underline{x}$. For low-observable targets, track-before-detect approaches are employed to integrate target energy to enhance target track detection. Dynamic programming (DP) and

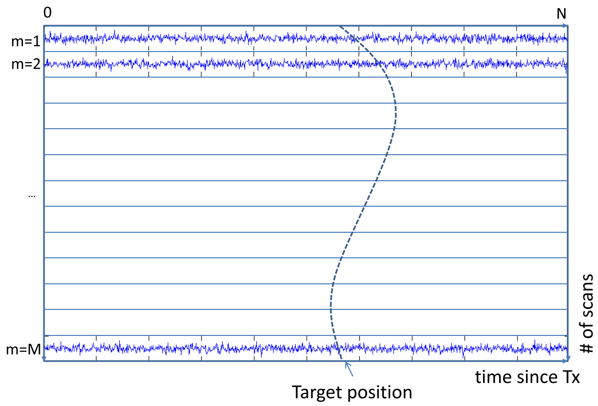

FIGURE 2. Entire observation.

particle filter (PF), two of the existing track-before-detect approaches, will be introduced, followed by the proposed track detection algorithm.

1) DYNAMIC PROGRAMMING

DP, well known for its application in sequence estimation as the Viterbi algorithm for hidden Markov models, is applied to TBD to find the overall maximum likelihood (ML) track by finding the maximum likelihood subsections of the overall track, recursively [22]. For each new update, likelihood values are computed for each hypothesized subsection of the track that terminate at the same state, or position. Subsequent subsection of tracks are appended to the previously determined maximum likelihood track.

The trade-off between performance and efficiency is realized by controlling the amount of time between each updates. Shorter update interval approaches conventional tracking and longer update interval leads to exhaustive search. For low-observable targets, it is difficult to avoid longer integration time without loss of performance. It has been illustrated in [4] that better fitting motion model can help alleviate the problem.

2) PARTICLE FILTER

PF assumes a hidden Markov model for the underlying state transitions, or the track evolution, and estimates the state sequence based on the updated posterior given the observations provided in each scan. States are the target positions as were described for DP. However, the difference is that only the distribution function is provided as the output in particle filtering and in dynamic programming states are discrete. PF can be applied in various ways depending on the assumptions made for the dynamic system, but the sequential posterior distribution update is the basis of the algorithm.

The two probabilistic models used in PF are the motion model, d_k, and the measurement model, z_k. The particles are sampled from the prior, which is evolved according to the motion model. With the observations and given the state of the particle, likelihoods are evaluated and used to construct the importance distribution. The importance distribution is used for the resampling, which is interpreted as the posterior given the observation.

As the SNR decreases, the true state is less likely to yield high amplitude, and thus likelihood. This makes it difficult for PF to estimate the true track in a sequential manner even when the integration of energy along the true track may have occurred. This is what the proposed method is designed to solve.

III. PROPOSED BATCH TRACK DETECTION APPROACH WITH MOTION MODEL

The proposed track detection algorithm is applicable to scenarios where longer decision delay is allowed for more reliable performance against low-observable targets. This approach is an extension of the TBD approaches in that it makes assumptions about the target motion, and hypothesizes many trial tracks, computes likelihood values based on how well it is supported by the data, then makes the decision toward the highest-scoring hypothesis. The performance gain comes from using an acceleration-based motion model for longer time scales. Details will be discussed in the following sections.

A. BATCH PROCESSING METHOD

The proposed batch processing algorithm consists of three steps. First, using the HMM motion model and pre-specified number of samples, sample trial target motions. Secondly, process the collected data using each of the trial motion and compute the likelihood. Lastly, find the trial motion that yields the maximum likelihood. This can be considered a special case of dynamic programming that uses a acceleration-based HMM for motion model, or a special case of particle filtering which assigns higher chance of sampling for more probable overall motion of the target. It is a random search approach that takes into account of the likelihood of the overall motion as well as the likelihood by examining the processed output magnitude.

Each random motion sample from the HMM motion model is a hypothesized overall relative motion between the target and the sensor that spans the duration of collected data. The number of trial is a parameter determined by acceptable computational load as well as the desired expected performance based on the expected SNR. Lower SNR target energy requires longer integration time, thus longer overall motion. Smooth overall motion assumption indicates low complexity motion, and this allows the search space to be manageable compared to exponentially growing search space for first-order Markov process.

Each trial motion, $\underline{x}$, describes the time evolution of the position as well as the velocity, $\underline{x}'$, associated with the motion of the target. As seen in Figure 2, the overall motion spans M scans. Each of M scans are processed with corresponding position and velocity of the motion, i.e., the scan is matched filtered with corresponding Doppler compensation and it is time-shift compensated to make the target energy in each scan coherently align with other scans. (3) and (4) are

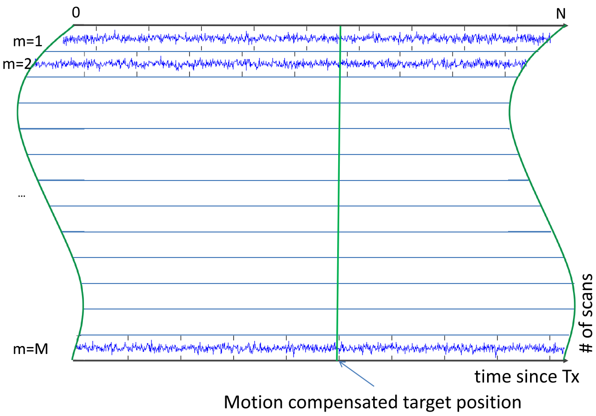

FIGURE 3. Aligned observation using the correct motion information.

the processed scan and the integrated output, with the argument scaled to represent range instead of time as in (1). Figure 3 shows an example where the target motion is perfectly compensated and the target echo arrivals from each scan are aligned to be coherently integrated. The true range cell accumulates all of the target energy and other range cells integrate noise. By concentrating the target energy into a small number of range cells, if not one, the output peak, O, has high peak-to-background contrast.

$$o_k(r) = z_k(r - x_k) = R_k(r - x_k) + v_k(r - x_k) \tag{3}$$

$$\begin{aligned} O &= \max\{\sum_{m=1}^{M} o_k(r)\} \\ &= \max\{\sum_{m=1}^{M} z_k(r - x_k)\} \\ &= \max\{\sum_{m=1}^{M} R_k(r - x_k) + v_k(r - x_k)\} \end{aligned} \tag{4}$$

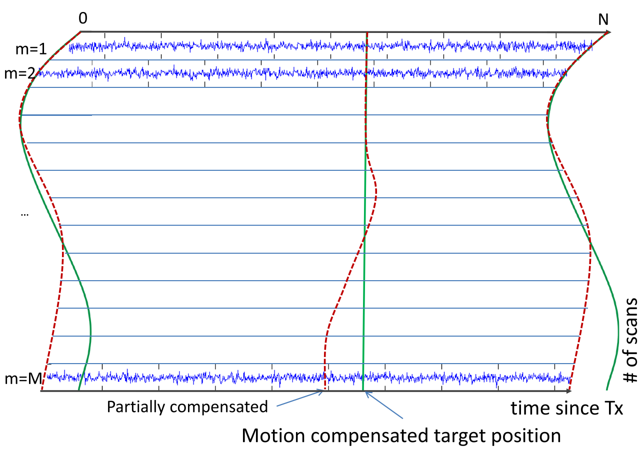

FIGURE 4. Processed with incorrect motion.

Figure 3 and Figure 4 show that a trial motion more similar to the true motion results in a higher contrast peak since the target energy is concentrated into a smaller number of range cells as a result of aligning the scans better. However, it should be noted that even when the alignment is not perfect, the peak contrast can still be high enough to be evident that there is significant amount of concentrated target echo energy. This indicates that the trial motions do not have to match the true motion exactly; as long as the trial motion is similar enough to the true motion, it results in a peak with high enough contrast. It should also be noted that the level of allowed dissimilarity of trial motion that would still produce a high enough contrast peak depends on the target echo energy level. If there isn't enough energy to accumulate even when the alignment is done perfectly, it will not produce a high-enough-contrast peak. More on this topic is discussed in III-D.

This leads to the third step of the algorithm. Since it is more likely for a trial motion more similar to the true motion to produce a higher contrast peak, the peak-to-background contrast is interpreted as a measure of the confidence, or the likelihood, of the trial motion. The higher the contrast, the more likely the true motion of the target is similar to the trial motion and therefore the confidence is higher in making a detection of the target track. Given the noise distribution, it is also feasible to set a threshold to the peak contrast above which a detection is made. In addition, overall track estimation is done simultaneously as the detection is made.

B. MOTION SIMILARITY

As illustrated by the comparison between Figure 3 and Figure 4, the shape of the overall trial motion determines the alignment of the target echo arrivals. More specifically, how similar the shape of the trial motion to the shape of the true target motion determines how well the target energy is integrated. In the context of the track detection algorithm described in section III-A, a motion similarity metric between two motions becomes useful for measuring how well target energy can be localized and for estimating the algorithm performance.

Similarity between two time series has been extensively studied as shown in surveys such as [23] and applied in [24]. These are mainly based on defining similarity in terms of the longest common subsequence (LCSS) [25]. The definition of similarity used in this work is not the same as LCSS, although similar in that it measures the proportion of the sequence where the difference is less than a specified tolerance.

The definition of similarity in the context of the proposed batch track detection algorithm is based on how similarly two different motions align and accumulate the target energy for all scans. For two motions $\underline{a}$ and $\underline{b}$, and arbitrary shifting parameter γ,

$$s(\underline{a}, \underline{b}) = \frac{1}{M} \max_{\gamma} \sum_{i=1}^{M} R(a_i - b_i - \gamma). \tag{5}$$

The value of the similarity metric $s(\underline{a}, \underline{b})$ spans from 0 to 1. Function $R(x)$ is the matched filtered and basebanded output normalized to have a peak value of 1, whose width is inversely proportional to the bandwidth of the transmitted waveform. Correlation width, w_c, is defined as the $3dB$ width of the function $R(x)$. It is known that larger bandwidth yields higher matched filter processing gain and higher range resolution [26], but high range resolution does not make it easier to align and accumulate target echo energy from multiple scans. As shown in Figure 4, the peak size of the processed output can be different for the same motion due to differences in correlation peak widths resulting from different transmission waveform bandwidths for each transmission. Therefore, motion similarity is dependent on w_c of each scan. The value of w_c is considered the tolerance of misalignment.

Note that the similarity is defined as the maximum sum of the function $R(x)$, where x is the difference between two motions being compared. Intuitively, this can be approximated as the maximum number of elements where x is smaller than w_c. Therefore, similarity is dependent on w_c. In the example shown in Figure 4, the output peak contrast for imperfect motion compensation is still high enough to be detected. However, when w_c is smaller, it makes the similarity measure more sensitive to variability of x and it may not accumulate to produce a high enough contrast peak.

The proposed batch algorithm takes advantage of the fact that a similar enough trial motion can still accumulate enough energy to make detection of the track. It relies on the smoothness of the overall motion of targets and the erratic nature of the motion of random clutter, on a large time scale. The algorithm also makes use of the fact that a hypothesized motion does not have to exactly match the actual target motion. Some overall mismatch is allowed and the level of allowed mismatch determines the efficiency of the batch algorithm.

Due to the mismatch tolerance, determined by w_c, there can be many different motions of the same overall trend with variations of small scale fluctuations. With large enough w_c, these realizations can be considered essentially the same motions in terms of alignment and target echo integration. Therefore, a motion model that does not produce redundant motions for a given value of w_c allows for more efficient performance of the proposed algorithm. This indicates a motion sampling method with improved efficiency, or achieving similar detection performance with less number of trial motions.

C. MOTION MODEL HOMOGENEITY

An important property of the motion model with respect to the proposed track detection algorithm is the homogeneity of sampled motions. A motion model is said to be homogeneous relative to w_c when the distribution of the similarity between random-pair motion-samples from the motion model have high similarity value and less pairs have low similarity value. On the contrary, if the pair-wise similarity distribution has more weight on lower similarity values, then the motion model is considered heterogeneous.

The batch algorithm performs random search in the motion space, with more weights in the more likely samples, and it is intuitive to forecast that when the actual target motion is included or is similar enough to what is described in the motion model, the probability of detecting the track is high. The algorithm relies on the typicality of the motion as well as the fact the trial motion does not have to exactly match the actual motion.

D. PERFORMANCE PREDICTION

In this section, an analytic expression of performance for the proposed method will be presented. The performance is dependent on SNR, length of motion or number of scans, M, and on the motion model homogeneity, h. Definitions of these terms will be presented, followed by the performance prediction.

Signal to noise ratio, or SNR, defined as

$$20 \log \frac{\sigma_S}{\sigma_N}, \tag{6}$$

is a function of target echo level, σ_S and the ambient noise level, σ_N. SNR is computed for each transmission, not for the overall integrated energy across multiple scans. The number of scans is denoted as M. Therefore, the total integrated target energy can be computed as $\sigma_S^2 \times M \times D$, where D is the transmission pulse duration.

As in section II-B, the motion model, H, is the probabilistic description of the target motion. Given each sampled motion, $\underline{x}$, associated with parameter λ, the conditional distribution function of similarity to other sample motions can be modeled as a truncated exponential distribution function expressed as,

$$f_S(s|H = \underline{x}) = \frac{\lambda \exp(-\lambda s)}{1 - \exp(-\lambda)}, \quad 0 \le s \le 1. \tag{7}$$

The parameter λ is dependent on the true target motion; negative λ value indicates trial motions are likely to be similar to the target motion, and positive λ value indicates trial motions are likely to be dissimilar to the sampled target motion, $\underline{x}$. A motion model with positive homogeneity, h, is when there are more true target motion samples are associated with negative λ value. In practice, homogeneity is likely to become smaller as M increases. However, the assumption in this paper is the motion of marine vehicles are well modeled with positive homogeneity. Figure 5 shows an example of $f_S(s)$ with negative λ value.

The performance metric in this paper is the probability of successful track detection. The criterion for success is defined in terms of the root mean squared error (RMSE) in order to make comparisons with other algorithms. Given an estimated track, $\underline{\hat{x}}$, and a threshold, ϵ, it is considered a success when,

$$RMSE(\underline{x}, \underline{\hat{x}}) = \sqrt{\sum_{m=1}^{M} (x_m - \hat{x}_m)^2} \le \epsilon. \tag{8}$$

To make the analysis tractable, it is assumed there is a one-to-one mapping between small-value region in RMSE and near-1 region in similarity, e.g., $\epsilon \simeq 0$ in RMSE corresponds to $\tau \simeq 1$ in the similarity metric, where τ is the threshold in similarity. In this analysis, it is considered a success when the maximum likelihood value associated

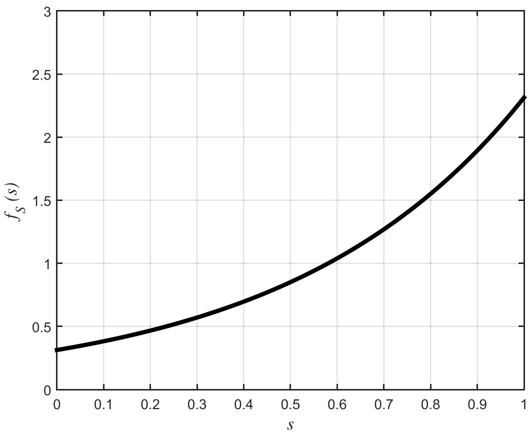

FIGURE 5. Distribution function of similarity to a true target motion with associated parameter value $\lambda = -2$.

with trial motions with $s \geq \tau$ is greater than the maximum likelihood value associated with trial motions with $s < \tau$.

Consider a trial motion with similarity s. The random variable representing the output likelihood associated with this trial motion is expressed as parametrized Normal distribution,

$$O(s) \sim N(Ms, M\frac{\sigma_N^2}{\sigma_S^2}). \tag{9}$$

With N sampled trial motions, the output likelihood values, O_n, are partitioned into two groups; $A = \{O_n : s_n \geq \tau\}$ and $B = \{O_n : s_n < \tau\}$. The number of samples in each group are N_A, N_B. It is considered a success when the maximum of A is larger than the maximum of B, assuming a trial motion with similarity to true motion close to 1 will yield a reliable integrated target energy. For convenience, the maximum output values are denoted as A_{max} and B_{max}. Therefore, the probability of success is,

$$Prob\{A_{max} > B_{max}\}. \tag{10}$$

The cumulative distribution functions (CDF) of maximum value of random variables with different underlying distribution functions, assuming independence, is expressed as the product of individual CDFs with different parameter values s_n,

$$F_{A_{max}}(o) = \prod_{n=1}^{N_A} F_{O_n|s_n}(o(s_n)), \tag{11}$$

$$F_{B_{max}}(o) = \prod_{n=N_A+1}^{N} F_{O_n|s_n}(o(s_n)), \tag{12}$$

$F_{O_n|s_n}(o(s_n))$ is an alternative expression of (9), and s_n values are determined by N and λ associated with the true target motion as,

$$s_n = \frac{\exp(\frac{\lambda n}{N}) - 1}{\exp(\lambda) - 1} \tag{13}$$

Note that N_A and $N_B = N - N_A$ can also vary with different true motions and associated similarity distribution function, (7), and the spacings between s_n's are inversely proportional to the PDF depicted in Figure 5. Those with $s_n \geq \tau$ contribute to (11) and those with $s_n < \tau$ contribute to (12).

$$f_{A_{max}|\lambda}(o) = \frac{dF_{A_{max}|\lambda}(o)}{do}. \tag{14}$$

Probability of successful Track Detection, P_{TD}, for a given σ_S and λ, using (10), (11), (12) and (14), is expressed as,

$$P_{TD}(\sigma_S, \lambda) = \int_O f_{A_{max}|\lambda}(o) F_{B_{max}|\lambda}(o) do. \tag{15}$$

The motion model, H, with respect to the distribution of similarity for different target motion samples, is modeled as another truncated exponential distribution function with the homogeneity parameter, h. It is the distribution function of λ values expressed as,

$$f_{\Lambda|h}(\lambda) = \frac{he^{-\frac{h}{2}}}{1 - e^{-h}} \frac{e^{\frac{h\lambda}{2\lambda_{max}}}}{2\lambda_{max}}, \quad -\lambda_{max} \leq \lambda \leq \lambda_{max} \tag{16}$$

Finally, using (15) and (16), the probability of success only dependent on σ_S is expressed as,

$$P_{TD}(\sigma_S) = \int_\Lambda \int_O f_{\Lambda|h}(\lambda) f_{A_{max}|\lambda}(o) F_{B_{max}|\lambda}(o) do d\lambda. \tag{17}$$

IV. RESULTS

A comparison between existing track-before-detect (TBD) methods, dynamic programming (DP) and particle filter (PF), and the proposed track detection algorithm will be presented with a simulation, followed by a comparison between the model prediction and the simulation for the proposed algorithm.

A. SIMULATION

The simulation set-up for comparing the proposed Batch Track Detection (BTD) algorithm to the two TBD methods, DP and PF, is as follows. For each trial, the overall target motion of length M, denoted as $\underline{x}$, is randomly sampled from the acceleration-based HMM. Target's echo energy, with a specified SNR, is inserted in the target position of each scan, x_m, a value from $\underline{x}$. The matched filtered and base-banded time series data is provided to each of the algorithms, DP, PF, and the proposed track detection method. Each algorithm produces an estimate of the track, $\hat{\underline{x}}$, and it is compared to the true track, $\underline{x}$.

The performance of tracking algorithms will be presented as a function of target SNR. The performance metric is defined as the probability of success for a specified SNR. It is considered a success when the root mean squared error (RMSE) between $\hat{\underline{x}}$ and $\underline{x}$ is smaller than the specified threshold, ϵ.

As seen in Figure 6, the performance of proposed batch track detection algorithm is higher than that of existing TBD methods at lower SNR values. Note that the performance gap is larger for longer tracks, $M = 400$, dotted lines. This illustrates how the proposed approach can perform reliably as

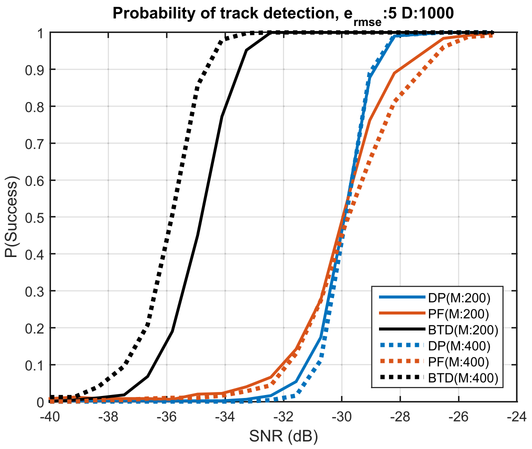

FIGURE 6. Track detection performance with varying SNR, pulse length: 1000.

long as the total integrated energy is high enough to yield a high-contrast peak, while TBD methods begin to fail once the SNR falls below a certain value.

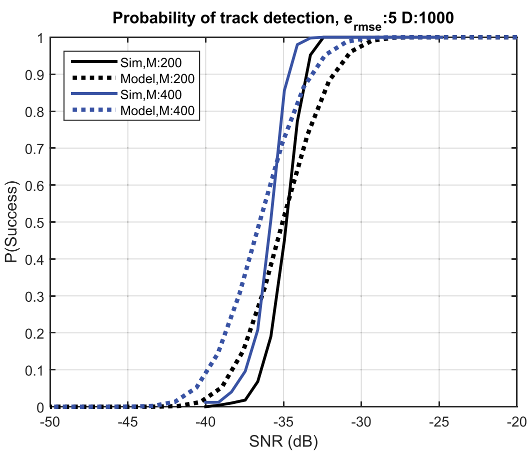

FIGURE 7. Track detection performance comparison between simulation and model. Solid lines are simulation and dashed lines are model. Black lines are with 200 transmissions and blue lines are with 400 transmissions).

Figure 7 compares the performance from the simulation with the prediction. The difference comes from the fact PDF of similarity does not match the actual distribution of measured similarity metric. However, the overall performance and its SNR dependence is captured in the prediction model.

V. CONCLUSION

A track detection method using an overall motion model is proposed for detecting low observable targets. This method is differentiated from dynamic programming (DP) or particle filter (PF) in that it computes the track likelihood based on integrated target energy for the entire hypothesized motion of the target sampled from a motion model in contrast to the sequential state update in DP and PF. Instead of the recursive state updates, this method employs a random search of the motion of the target for the entire duration of the observation.

The motion model is an acceleration-based Hidden Markov model similar to the Singer's acceleration dynamic model and it allows the random search to be computationally feasible. With exhaustive motion space search using first-order Markov process, the search space grows exponentially with the number of transmissions. Here, a smooth motion assumption is made using the acceleration-based HMM. The realistic assumption of marine vehicle motion allows for efficient sampling and the processing algorithm also allows for a level of mismatch associated with the correlation width, w_c.

Comparison of the proposed method to existing TBD methods is shown in terms of the probability of successful detection of track against target echo SNR. Given that the target motion matches the proposed motion model, while the recursive method fails to accumulate enough energy to make a reliable track estimates for very low SNR targets, the proposed method is able to coherently integrate the target echo energy and detect the true track at lower SNRs.

Using motion similarity and motion model homogeneity, a performance prediction model is derived and agrees with the simulation results. Some assumptions and approximations allow for intuitive interpretation of the prediction model and provides insight as to how the algorithm performs.

VI. DISCUSSION AND FUTURE WORK

As shown in Figure 7, the performance of the proposed approach depends on the similarity distribution for each true target motion. Since the algorithm is a model-based signal processing approach, performance is predictable when the assumption on motion model matches the reality. However, it begins to deviate when the model fails to make correct assumptions. The effect of model mismatch is the topic of current effort and will be investigated both empirically with simulations and analytically, using the similarity distribution functions.

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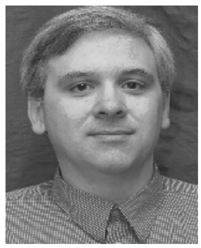

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