I. INTRODUCTION

High resolution radar (HRR) generates data sets that have significantly different properties from other data sets used in automatic target recognition (ATR). Even if used to form images, these images do not normally bear a strong resemblance to those produced by conventional imaging systems. Data are collected from targets by illuminating them with coherent radar waves, and then sensing the reflected waves with an antenna. The reflected waves are modulated by the reflectivity density of the target. Despite the widespread use of HRR, there are many open issues with regard to its use in ATR systems. Some of these issues are reviewed here and discussed in the context of a set of actual S-band range-profiles.

This paper describes a framework for jointly tracking and recognizing aircraft from HRR range-profiles. A likelihood function for a sequence of HRR range-profiles is obtained through the combination of a likelihood function for the observations conditioned on the target type and the sequence of target orientations, and a dynamics-based prior on those orientations given the target type. The derivation of this likelihood function is first given in general terms, then specific simplifying assumptions are invoked to make the result more computable. The most difficult issue from a modeling viewpoint is whether the range-profiles should be modeled as deterministic (as is traditional in the electromagnetics literature) or stochastic (as is more common in the signal processing literature). This issue is explored and simulations using two possible models are presented.

The data model presented here has its roots in pattern theory as pioneered by Ulf Grenander [5, 6]. In this theory, the data are modeled as a transformation of an underlying template to the observation space, plus noise. The transformation here consists of model selection and the sequence of rigid body motions defining the target trajectory. Inference on this space of transformations has two parts. Inference on the model selection parameter is equivalent to target recognition. Inference on the positions and orientations is equivalent to tracking, or state estimation in the dynamical model.

The algorithms described herein have as their roots the jump-diffusion based random sampling algorithms proposed by Miller and Grenander [6, 13]. This algorithm has been proposed for use in automatic target tracking and recognition problems by Miller, et al. [13, 14, 20]. These algorithms construct Markov chains on the mixed discrete-continuous transformation space whose unique stationary measure is the posterior given the observed data. Means under the posterior may then be computed via time averages of functions of the Markov chain. The diffusion component samples over continuous parameters while
the discrete jump component searches over discrete parameters including model order and target type.

Our approach is different from other approaches proposed in the literature. The key to its success is how well the HRR range-profile likelihood function models real data. By giving the derivation in general terms, we allow for the possibilities that either the deterministic or the stochastic model presented or some other model is best for the data. In fact, it may be true that for a specific target, one model is more appropriate at some frequencies, and another model is more appropriate at other frequencies. Whatever model is appropriate for a given frequency band, the theory here gives a likelihood function for the entire sequence of HRR range-profiles, so that recognition is not performed on a per-range-profile basis.

A. Recognition Problem

The methodology in this paper and in related efforts [6, 13, 14, 20] can be applied to the problem of detection, tracking, and recognition of multiple targets by an automated system. In the most general formulation of the problem, multiple sensors view a time-evolving scene. Noncooperative targets enter and leave the scene at unannounced times. Based on low and high resolution observations, inferences are drawn on the kinematic states of the targets and eventually the target types.

We concentrate on the problem of recognition of a single noncooperative moving target. Note that the target is assumed to have been detected. In this case, the problem is to track the position and orientation of the target, and to recognize the target, from the observations of both a tracking radar and an HRR. The observations are made at the sample times \( \tau_1, \tau_2, \ldots, \tau_K \) over an interval \([t_1, t_2]\). The target positions and orientations at the sample times are given by \( \{p_k \in \mathbb{R}^2; k = 1, 2, \ldots, K\} \) and \( \{\theta_k \in SO(3); k = 1, 2, \ldots, K\} \), respectively. For a target undergoing arbitrary motion in 3 dimensions, the orientation \( \theta \) is parameterized by a 3 × 3 rotation matrix taking its value on the special orthogonal group \( SO(3) \). For ground targets with a known ground plane, \( \theta \in SO(2) \), which can also be parameterized by a single Euler angle taking its value on a circle. The target type is denoted by \( a \in A \), where the set \( A \) is an exhaustive list of candidate target types. For a given set of observations, the parameter set to be estimated, known as a target trajectory, consists of the target position and orientation (a point in \( \mathbb{R}^3 \times SO(3) \)) at each of the \( K \) observation times and the target type (an element of \( A \)). Hence the target trajectory can be represented by an element of the space

\[
(R^3 \times SO(3))^K \times A.
\]  

This space is of dimension \( 6K + 1 \), since there are three position variables and three orientation variables for each of the \( K \) observation times. The one additional dimension is discrete-valued and corresponds to the target type.

At the \( k \)th observation time, the tracking radar produces the vector \( y_k \), which may correspond to measurements from a radar array, or more traditionally, measurements of the azimuth, elevation and range to the target. At these same times, the target is illuminated by a sequence of radar pulses, and the received echoes, known as range-profiles, are collected. Let \( r_k(t) \) denote the \( k \)th range-profile, that is, the waveform at the output of the radar receiver for the \( k \)th illumination. The collection of tracking data vectors \( Y \) and range-profiles \( R \), and the sequences of positions \( P \) and orientations \( \Theta \) up to the time of the \( k \)th measurement are given by

\[
Y_k = \{y_1, y_2, \ldots, y_k\} \quad P_k = \{p_1, p_2, \ldots, p_k\} \quad R_k = \{r_1(t), r_2(t), \ldots, r_k(t)\} \quad \Theta_k = \{\theta_1, \theta_2, \ldots, \theta_k\}.
\]  

The joint posterior density for the parameters conditioned on the observations is decomposed through Bayes’ rule into the product of the prior density \( p \) on the parameters and the likelihood function \( \Lambda \) for the observations given the parameters,

\[
p(P_k, \Theta_k, a \mid Y_k, R_k) \propto p(P_k, \Theta_k, a) \Lambda(Y_k, R_k \mid P_k, \Theta_k, a).
\]  

Because the parameters \( P_k \) and \( \Theta_k \) and observations \( y_k \) and \( r_k(t) \) occur sequentially, we may write

\[
p(P_k, \Theta_k, a \mid Y_k, R_k) \propto p(P_0, \Theta_0, a) \prod_{\ell=1}^{k} p(P_{\ell}, \theta_{\ell} \mid P_{\ell-1}, \Theta_{\ell-1}, a) \times \exp(L(y_{\ell}, r_{\ell} \mid Y_{\ell-1}, R_{\ell-1}, P_{\ell}, \Theta_{\ell}, a))
\]  

where \( p(P_0, \Theta_0, a) \) is a prior on the initial position, orientation, and target type, \( p(P_{\ell}, \theta_{\ell} \mid P_{\ell-1}, \Theta_{\ell-1}, a) \) is a prior on the \( \ell \)th position and orientation given all previous positions and orientations and the target type, and \( L(y_{\ell}, r_{\ell} \mid Y_{\ell-1}, R_{\ell-1}, P_{\ell}, \Theta_{\ell}, a) \) is the log-likelihood of the \( \ell \)th tracking vector and the \( \ell \)th range-profile, given all previous observations, the first \( \ell \) positions and orientations, and the target type. In the notation for the log-likelihood function, the dependence of \( r_{\ell} \) on \( t \) is omitted, because the log-likelihood does not depend on the value of \( r_{\ell}(t) \) at a given time, but at all times.

In the case of a deterministic model for \( r_{\ell}(t) \) or conditionally independent observations (see Section IV), with \( Y \) and \( R \) conditionally independent given \( P_k \) and \( \Theta_k \), the posterior is proportional to the product

\[
p(P_k, \Theta_k, a \mid Y_k, R_k) \propto p(P_0, \Theta_0, a) \prod_{\ell=1}^{k} p(P_{\ell}, \theta_{\ell} \mid P_{\ell-1}, \Theta_{\ell-1}, a) \times \exp(L(y_{\ell} \mid p_{\ell}) \exp(L(r_{\ell} \mid \theta_{\ell}, a))
\]
where \( L(y_t | p_t) \) is the log-likelihood of the \( t \)-th tracking data vector given the \( t \)-th position, and \( L(r_t | \theta_t, a) \) is the log-likelihood of the \( t \)-th range-profile, given the \( t \)-th orientation and the target type. Note that in this formulation, we assume that the tracking data are low resolution and are insensitive to target type and orientation. This assumption is valid if all targets have approximately the same statistics for their radar cross-sections (RCS) at the frequency of the tracking radar, and these cross-sections have approximately the same statistics for arbitrary orientation bins. This formulation also assumes that the HRR range-profiles are invariant to target position, but do depend on target orientation. The position invariance is valid in the cross-range dimension if the target is in track and is smaller than the beamwidth of the transmitting antenna. The bulk range to the target does enter the likelihood through the signal-to-noise ratio. Fine range shifts can be inferred from the range-profiles, and are less of an issue than orientation estimation. The prior \( p(p_t, \theta_t | P_{t-1}, \Theta_{t-1}, a) \) is derived from an appropriate dynamical model for the target motion. It is the introduction of target dynamics which makes tracking and recognition inseparable. In part, it is this fundamental link which has motivated us to propose solving the tracking and recognition problems in a single consistent estimation framework in which the inference proceeds via the fusion of multisensor data. In the simulations of Section V, we consider simplified dynamical models that allow us to place deterministic constraints on the sequence of estimates produced by our algorithm.

It is also be useful to consider a simplified problem in which the target is assumed to be in track already, and only data from a single HRR sensor are available. In this case, the dynamical model used could be the residual error from a low-resolution tracker. Alternatively, the tracking information derived as part of the inference may be used to drive the pointing of the sensor and to keep the target in track. In either case, the target trajectory to be estimated can be represented by a point in the space

\[
SO(3)^K \times A
\]

and the posterior simplifies to

\[
p(\Theta_T, a | R_T) \propto p(\Theta_0, a) \prod_{t=1}^K p(\theta_t | \Theta_{t-1}, a) \exp(L(r_t | \theta_t, a)).
\]

Note that in this formulation, the prior \( p(\theta_t | \Theta_{t-1}, a) \) is on the orientation only.

Of crucial importance to the performance of an estimator for this problem is the behavior of the data log-likelihood \( L \) for varying orientations and different target types, which in turn depends on the model chosen for HRR data. A primary factor making recognition from range-profiles difficult is the extreme variability in the observed data for small changes in target orientation. This represents a considerable modeling challenge as the model must accurately predict the variation, but the resulting recognition algorithm should be robust with respect to this variation.

The remainder of this paper investigates a variety of issues relating to the utility of HRR data in target recognition. Section II presents a review of the open literature concerning ATR algorithms and the role of HRR data. In Section III we present an analysis of real S-band range-profiles both supporting the potential for recognition and indicating some of the difficulties. The choice of possible radar data models and the relative merits of two candidate models are discussed in Section IV. In Section V we describe simulations in which joint orientation estimation and recognition are performed. Finally, Section VI presents our conclusions and directions for future research.

II. LITERATURE REVIEW

A. Algorithms for ATR using HRR Data

Over the years, authors have proposed a variety of algorithms for performing ATR using HRR data. This section discusses several efforts appearing in the literature that are closely related to our approach.

Ksienski, et al. [10] propose a target identification scheme based on multifrequency measurements of the RCS. Classification of a target is performed either by a linear discriminant, in which the data space is divided into class-specific regions by hyperplanes, or by a nearest neighbor technique, in which classification is achieved by comparing an observed range-profile to a library of signatures recorded for a discrete set of aspect angles. The nearest neighbor technique assumes knowledge of the orientation which resulted in the observation. This is the earliest effort we have encountered in the literature in which objects are classified directly from their radar reflections, without first performing feature extraction.

Chen, et al. [2] extend the multifrequency RCS method by comparing measurements and stored library elements not only directly in the frequency domain but also in the time domain through preprocessing using the inverse discrete Fourier transform. Classification in the frequency domain uses a nearest neighbor decision rule. Time domain classification is performed by maximizing the correlation between observed and prestored data. As with Ksienski, the orientation which resulted in the observations is assumed known.

Libby [11, 12] provides a detailed comparison of six algorithms for orientation estimation and target identification within a general dynamic-programming
structure. A particular aircraft model is chosen, along with true position and orientation states of the aircraft over time. The orientation states are used to select a sequence of HRR signatures from a library of simulated returns. Next, range, range rate, and pointing angle measurements are provided to a Kalman-filter tracking algorithm, which provides estimates of the complete kinematic state of the target. Dynamic programming is applied to estimate the sequence of orientations corresponding to the sequence of observed HRR signatures. The results of these experiments show that an algorithm in which the orientation sequence is modeled as a Markov chain exhibits superior performance in terms of a minimum computed likelihood for the incorrect target model, as compared with other algorithms.

An application of orthogonal subspace projection methods to recognition of aircraft from range-profile data is presented by Zyweck [23–25]. In this work, range-profiles were collected from Boeing 727 and 737 aircraft over a 50 deg sweep in aspect angle as they took off from Adelaide Airport in Australia. The authors apply a number of preprocessing steps to the range-profiles prior to classification, including range alignment, averaging, thresholding, and computation of the discrete Fourier transform. The resulting feature vectors are divided into training and testing sets, and the training set for each aircraft is used to compute a single basis vector using Fisher’s Linear Discriminant. The training vectors are then projected along this basis vector, and the mean and variance for each aircraft are computed. Recognition of a feature vector from the testing data set is performed by projecting it along each basis vector, computing the Gaussian likelihoods for each aircraft, and performing a likelihood ratio test. The results of their test indicate a 96% rate of correct recognition for this two-class problem. This result is significant because a high rate of recognition was achieved using actual radar data, and the algorithm achieved correct recognition for variations in aspect angle of 50 deg. It is difficult to say whether the techniques employed here would also be successful when attempting to distinguish a greater number of targets over a broader range of aspect angles.

The adaptive Gaussian classifier or AGC is a system developed by Hughes Aircraft Corporation for recognition of noncooperative targets from HRR range-profiles currently under study by the Air Force Wright Laboratory. Observed range-profiles undergo several preprocessing steps prior to classification, including computation of the magnitude in each range bin, downsampling, coarse range alignment, normalization to unit signal energy, and power transformation. The power transformation step is defined by [4, 15]

$$d[i] = (c[i])^{0.4}$$  \hspace{1cm} (8)

where $c[i]$ is the return in range bin $i$ after energy normalization and $d[i]$ is the same return after the power transformation. The rationale here is that the processed range-profiles are assumed to be distributed according to a Rician probability density function, and that the transformation of (8) "make[s] the underlying UHRR radar pdf more closely appear Gaussian," [4] so as to validate the use of the Gaussian log-likelihood. Classification of range-profiles is performed by comparison with templates developed over 5° x 5° patches in azimuth and elevation angles for each target [1]. Each template consists of a mean value $\mu[i]$ and a variance $\sigma^2[i]$ of the returns in each range bin $i$. The AGC does not estimate target orientation from the observed range-profiles, even though the available templates might allow for such estimation. It is assumed that orientation estimates are provided by an external system. Therefore, classification consists of computing the Gaussian likelihood energy for each target class given by

$$\ln |\hat{\Sigma}| + (\hat{x} - \hat{\mu})^T \hat{\Sigma}^{-1} (\hat{x} - \hat{\mu})$$  \hspace{1cm} (9)

where $\hat{x}$ is the received range-profile, $\hat{\mu}$ is the template mean for a given target class and the known orientation, and $\hat{\Sigma}$ is the diagonal covariance matrix whose non-zero entries are $\hat{\sigma}^2[i]$. The template that minimizes the likelihood energy is selected as the target type estimate for range-profile $\hat{x}$.

A. Discussion of Viability of ATR Using HRR Data

It is widely accepted that HRR data in the form of a range-profile are properly described as a time signal that is parameterized by the target shape and orientation during illumination. While a definitive model for the orientation dependence has yet to be published, it has been known for some time that range-profiles are very sensitive to small changes in orientation. This sensitivity has led some authors to suggest that HRR data are not appropriate for target identification. This section reviews some of these arguments.

Skolnik [17] considers the variation with orientation of the RCS of complex targets, including a B-26 bomber rotated on a turntable. Skolnik notes that the cross-section can change by as much as 15 dB when the azimuthal angle is changed by only $\frac{1}{2}$ deg.

Cohen [3] reports the results of computing the RCS as a function of azimuth for a wireframe model of an aircraft and indicates that sampling on a scale smaller than 1 deg is necessary to represent the variation. Additional computations are performed on a simple model of an engine assembly, leading to the statement that "the RCS completely decorrelates every 0.2" deg, and indicating that the template library needed for recognition.
of all the world’s aircraft would consist of some 100 gigabytes of data. In a contradictory analysis, plots are shown which indicate that range-profiles simulated for a particular aircraft at an angular separation of as much as 5 deg have significant similarity in their shape, although the amplitude varies greatly. Also, an experiment is reported in which identification was successfully performed using templates stored every 1 deg in aspect angle.

The mechanism responsible for speckle or scintillation in radar returns, as reported variously in [3, 16, 17], is typically described in terms of phase cancellation. Consider monochromatic illumination of a radar target by a source of wavelength \( \lambda \). The reflected field is the sum of reflections from all points on the target. If the orientation of the target is changed so that points in the same range bin move through a distance on the order of \( \lambda \), the relative phases contributing to the complete return produce varying degrees of constructive and destructive interference over the rotation. If the target is large compared with \( \lambda \), then the rotation required to produce speckle is very small.

Other authors [11, 18, 21] have made various intuitive statements regarding the orientation scale over which the range-profile undergoes significant change and the implications for ATR.

What is lacking from all these attempts is sufficient data from which to draw firm conclusions. Given that we employ a likelihood-based algorithm for ATR, our investigation of the potential of HRR data for use in recognition is based on examination of the likelihood surfaces for varying orientations and different target types. In later sections, we examine these surfaces for two range-profile models and describe properties that these surfaces must exhibit if recognition is to be performed using HRR data.

III. HRR DATA EXAMPLE

HRR data were collected in an experiment performed by Rome Laboratory in which targets of opportunity were illuminated by an S-band radar. The transmitted signal was a linear FM chirp, with a center frequency of 3.4 GHz and a bandwidth of 320 MHz. Vertical polarization was used during transmission and reception. Each data set consists of 119 range-profiles collected over a time interval of less than 1 s, with successive range-profiles occurring approximately 4 ms apart. The change in the orientation of the illuminated aircraft with respect to the radar system between adjacent range profiles is exceedingly small. Therefore, one might expect that the range-profiles for a particular aircraft would be very similar to one another.

The left panel of Fig. 1 displays the magnitude of 119 range-profiles from one of the data sets for a DC-10 aircraft. The self-consistency of the range-profiles in this data set is evident in that the individual traces which make up this plot lie nearly on top of one another. This consistency is also portrayed in the right panel of Fig. 1 which shows the magnitude of the correlation computed between 24 pairs of range-profiles drawn from this data set. The smoothness of this plot indicates that the change between successive range-profiles in this data set is also smooth. Apparently, the sensitivity of the range-profile to small changes in orientation is not so extreme that the minutely different orientations achieved by the DC-10 during the collection of these data result in drastically different range-profiles.

Fig. 2 displays a result which both supports the potential to discriminate among different target types using range-profile data and indicates some of the difficulties. Here, the traces in the upper portion of the figure are simply the correlation matrix of Fig. 1 when viewed from the side. The next lower group of traces
Fig. 2. Correlation of range-profiles from 3 aircraft. Upper group of traces show inner product between pairs of range-profiles from DC-10 data set. Middle group shows inner product of range-profiles from DC-10 with DC-9 data set. Lower group shows inner product of range-profiles from DC-10 with Cessna 310 data set.

represent the result of correlating the same DC-10 range-profiles with 24 range-profiles observed from a DC-9 aircraft. The lowest group of traces represent the result of correlating DC-10 range-profiles with those collected from a Cessna 310. The range-profiles from the DC-10 are significantly more highly correlated with each other than they are with range-profiles collected from the other two aircraft. This suggests that identification could be performed using these data with an identification statistic as simple as the inner product. However, note that over only a 1 s interval, the DC-10 range-profiles decorrelate down to around 85 percent. This is quite a change over a relatively short time interval with very little aspect change in the target. One challenge is to develop a more robust approach that captures the features of the range-profile without being sensitive to the variations over small orientation changes. As discussed below, the conditionally Gaussian model achieves this.

IV. MODELS FOR HRR DATA

Fundamentally, the question of modeling HRR data should be addressed from a physics viewpoint. One of the premises behind the development of a signature prediction tool like XPATCH (which is used here and is described in Section IVA) is that the range-profile is computable given the target orientation. This has been the overriding viewpoint of the electromagnetics community for this problem. This may or may not be physically accurate. Even ignoring propagation effects, an airframe flexes during flight introducing variations in the range-profiles by changing the distances between scatterers by more than a wavelength. This flexing itself or vibrations in ground targets may be enough to invalidate a deterministic model. Other physical effects such as moisture or dirt on the vehicle and control surface movement are not adequately modeled by signature prediction tools. These indicate that stochastic models (based in large part on the outputs of tools such as XPATCH) may be best for HRR range-profiles.

There is also the quantitative issue of how many range-profiles must be stored if a deterministic model is adopted. One answer outlined next says that the number grows quadratically with the carrier frequency. For increasing carrier frequencies, the memory and processing capabilities must grow quadratically to maintain similar performance. There clearly will be a point, reached at rather modest frequencies, at which these requirements will become so demanding that the use of a deterministic model is no longer feasible.

The target may be viewed as being space-limited (even accounting for jet engine modulation and late cavity returns). Thus, the sampling theorem specifies the sampling density necessary in the frequency domain for perfect reconstruction of a three-dimensional model of the target in spatial coordinates. This spatial domain model of the target may not look like a three-dimensional computer-aided design model of the target, but it characterizes the range-profiles observed. Each range-profile corresponds to a radial line-segment in three-dimensional Fourier space, going through the carrier frequency with length equal to the bandwidth of the transmitted signal. To satisfy the sampling theorem, these line segments must be spaced with fixed separation independent of the
carrier frequency. To achieve this, the number of line segments in Fourier space (which equals the number of range-profiles for near-perfect reconstruction) must grow quadratically with the carrier frequency. This number represents a discrete sampling of the possible orientations producing distinct range-profiles, which under many models is a set of points on the surface of a sphere [8]. If these points are approximately equidistant, then the angular separation between adjacent orientations is inversely proportional to the carrier frequency.

The two models considered here are extremes within the family of Gaussian random process models. At one extreme, the range-profiles are modeled as being deterministic, and thus are completely known given the target type, position, and orientation. When viewed as a Gaussian random process, this model has mean given by the modeled range-profiles and a covariance of zero. In a sense, these range-profiles have perfect correlation. At the opposite extreme, the range-profiles are modeled as being independent from range bin to range bin and from one orientation to another. If all means are zero in this extreme, then the resulting range-profiles have no correlation in the sense that a range-profile at one orientation is uncorrelated with an observation of a range-profile at another orientation. In between is a continuum of other possible models with varying degrees of correlation structure assumed. The intermediate possibilities are not addressed here, but are considered in other efforts by the authors [9].

Assuming that the available data are
\[ r(t) = s(t; \theta, a) + w(t) \]  
(10)
where \( s(t; \theta, a) \) is the signal and \( w(t) \) is additive complex white Gaussian noise, the issue is the model used for \( s(t; \theta, a) \). Under a Gaussian assumption, given the target type \( a \), \( s(t; \theta, a) \) is a complex Gaussian random process with mean \( \mu(t; \theta, a) \) and covariance determined by
\[ K(t_1, t_2, \theta_1, \theta_2 | a) = E\{[s(t_1; \theta_1, a) - \mu(t_1; \theta_1, a)] \times [s(t_2; \theta_2, a) - \mu(t_2; \theta_2, a)]^*\}. \]  
(11)

The process \( r(t) \) is typically not available as a continuous-time waveform in real radar systems; only a sampled version is available. A discretized version of (10) is given by
\[ \mathbf{r} = \mathbf{s}(\theta, a) + \mathbf{w} \]  
(12)
where the sampling is assumed to result from integration of \( r(t) \) against orthonormal functions. The entries of \( \mathbf{w} \) are then independent complex Gaussian random variables with mean 0 and variance \( \mathbf{N}_w \); \( \mathbf{s}(\theta, a) \) is a complex Gaussian random vector with mean vector and covariance matrix determined by the model assumed for the underlying continuous process and the sampling functions used. From this point forward, we use this vector notation, with a bold-faced \( \mathbf{r} \) or \( \mathbf{r}_k \) denoting a range-profile vector.

When possible, range-profile data are typically calibrated so that the squared magnitude of the return in each range bin represents a measurement of the RCS of that portion of the target. For consistency with this practice, we express the squared magnitude of any element of \( \mathbf{r} \) and the noise variance \( \mathbf{N}_w \) in units of square meters.

A. Deterministic Model and XPATCH

Under a deterministic model, the vector \( \mathbf{s}(\theta, a) \) is known given \( \theta \) and \( a \). The log-likelihood for \( \mathbf{r} \) is then
\[ L(\mathbf{r} | \theta, a) = \frac{2}{\mathbf{N}_w} \text{Re}\{[\mathbf{r} - \frac{1}{2} \mathbf{s}(\theta, a)]^* \mathbf{s}(\theta, a)\} \]  
(13)
where \([\cdot]^*\) denotes the Hermitian transpose. The use of (13) requires a database of range-profiles stored on a grid in orientation space. The sampling on this grid is determined by the smallest angle over which range-profiles decorrelate. As discussed above using sampling theory arguments, this angle is inversely proportional to the carrier frequency. Given a sequence of measured vectors \( \mathbf{r}_k \) corresponding to a sequence of target orientations as the target undergoes a maneuver, the joint likelihood function is obtained as a product of the likelihoods of the individual vectors.

The validity of a deterministic model is assumed by many who develop signature prediction tools such as XPATCH. XPATCH is a computer software package developed jointly by Wright Laboratory and DEMACO, Inc., that is designed to simulate the radar return from a given target. The target is represented by a collection of triangular patches and outward normal vectors. The algorithm is based on the shooting and bouncing ray technique, in which rays are directed from the radar toward the target, and traced as they bounce off of and around the various patches on the target. Those rays which are eventually directed back toward the radar contribute to the return. This technique allows for incorporation of the effects of both shadowing and multibounce. When simulating the range-profile for a particular target, the algorithm is invoked to simulate the complex scattered far-field at discrete frequencies that are uniformly spaced within the specified transmitter bandwidth. The range-profile is found from the frequency-domain data through the inverse Fourier transform.

B. Conditionally Gaussian Model

The stochastic model we use assumes that range-profiles are independent from one orientation to another and that for each orientation, the values
in the range bins are independent complex Gaussian random variables. Assume that the dimension of \( r \) is \( M \), that the \( m \)-th entry is \( r(m) \), and that the mean and variance of the \( m \)-th entry are \( \mu(m; \theta, a) \) and \( \sigma^2(m; \theta, a) \), respectively. Then the log-likelihood for \( r \) is

\[
L(r | \theta, a) = - \sum_{m=1}^{M} \left[ \ln(\sigma^2(m; \theta, a) + N_0) + \frac{|r(m) - \mu(m; \theta, a)|^2}{\sigma^2(m; \theta, a) + N_0} \right].
\]

There are several possible assumptions on \( s(t; \theta, a) \) that would yield independence of the range samples. One is that the sampling is performed by integrating \( r(t) \) against eigenfunctions of the autocorrelation function for \( s(t; \theta, a) \). Another is that \( s(t; \theta, a) \) is uncorrelated with itself at different times \( t \) and different orientations \( \theta \),

\[
K(t_1, t_2; \theta_1, \theta_2 | a) = K(t_1, \theta_1 | a) \delta(t_1 - t_2) \delta(\theta_1 - \theta_2)
\]

and that sampling uses nonoverlapping rectangular pulses. This second assumption is an extension of the standard wide-sense stationary uncorrelated scatterer (WSSUS) model discussed by Van Trees [22].

The use of the conditionally Gaussian model requires a database of mean and variance vectors. These should be stored on a grid in orientation space just as the range-profiles in the deterministic case are stored on a grid. However, as discussed in related work [9], the angular sampling can be much more sparse than in the deterministic model, and does not necessarily increase in proportion to the carrier frequency. The main requirements are that the likelihood of any range-profile in an orientation bin should be approximately constant over the bin, and the spacing between bins should be large enough that the range-profiles are approximately independent. The first requirement motivates an adaptive method to choose the size of sampling bins based on the deviation of the resulting likelihood values. We concentrate on choosing regular bin sizes and estimating the mean and variance vectors for each bin as sample means and variances.

C. The URISD

The University Research Initiative Synthetic Dataset (URISD) is a collection of simulated range-profiles produced by the HRR simulator XPATCH. The URISD includes range-profiles simulated for four ground vehicles (two tank models, school bus, fire truck) over three frequency bands (UHF, L, X) and at three different elevation angles (10°, 25°, 40°). Each vehicle is represented by a CAD model consisting of triangular patches covering the surface of the vehicle and a simulated rough ground surface, included so that the range-profiles exhibit the effects of reflections from the terrain in the vicinity of the vehicle. The tank models are generic in nature and are not intended to represent any particular existing tank; they are assigned the arbitrary labels of “m1” and “t1.” The 36 data sets comprising the URISD each contain range-profiles for target azimuth angles that are uniformly sampled around the circle at a density that depends on the frequency band. Additionally, the data sets contain range-profiles simulated for each of the four combinations of transmitted and received linear polarization states, \( \{hh, hv, vh, vv\} \). The parameters for the various data sets are summarized in Table I.

We have made use of these data in developing a simulation of joint tracking and recognition that is presented in Section V. Additionally, these data were used in a number of simple tests to compare the recognition performance associated with candidate HRR models and the associated likelihood functions.

D. Model Comparison Via Likelihood Functions

We have made a comparison of the two HRR data models at both L-band and X-band for the purpose of evaluating the potential for target recognition under each model. Range-profiles were drawn from the URISD, and the log-likelihood function was computed under each model for varying orientations and target types. We selected a subset of the \( vv \) range-profiles for each of the four targets at an elevation of 10 deg and for azimuth angles over the range of 10 to 30 deg. A sampling of the L-band range-profiles is depicted in Fig. 3.

As evidenced by the figure, the range-profiles produced by XPATCH exhibit extreme variability for small changes in azimuth angle. To test whether this variability allows for the use of these data for recognition, the range-profile from the fire truck dataset at an azimuth angle of 19.95 deg was selected as an observation, and the log-likelihood functions under the deterministic model (13) and the conditionally Gaussian model (14) were computed for each of the four vehicles over the range of azimuth angles from 10 to 30 deg. When evaluating the Gaussian log-likelihood function, mean and variance vectors were computed by averaging over 3 degree orientation bins for the L-band data, and over 1 degree
The results of this test are depicted in Fig. 4. The upper panels show the log-likelihood under the deterministic model, while the lower panels show the log-likelihood under the conditionally Gaussian model. In all panels, the solid line shows the log-likelihood for the correct vehicle, the fire truck. Note that no noise was added to the observation prior to conducting this test. However, to avoid division by zero, we have computed the log-likelihood functions for both models using an artificial noise variance of $N_0 = 0.01 \text{ m}^2$. Thus, while the actual signal-to-noise ratio for the observations used here is infinite, we may interpret the plots of Fig. 4 as depicting the expected value of the log-likelihood function over the ensemble of realizations of the noise process, for an SNR of 35 dB in the case of the L-band data and 49 dB in the case of the X-band data.

The results of this test show that recognition is possible using either model, in that the likelihood of the correct vehicle in the vicinity of the true azimuth angle is larger than the likelihood for any of the incorrect vehicles. However, note that under the deterministic model for the L-band data, the azimuth angle must be estimated to within ±0.5 deg of the truth for recognition to be successful. In contrast, correct recognition is achievable under the Gaussian model even when the azimuth is in error by as much as 10 deg. These results are in accordance with previous simulations using other targets.

Under the deterministic model for the X-band data, the azimuth angle must be known to within 0.1 deg of the truth for correct recognition. Under the Gaussian model, recognition performance is robust with respect to significant errors in azimuth estimation. However, it is not the case that the log-likelihood function for the correct vehicle is entirely insensitive to the target azimuth. The plot shown in Fig. 4 appears flat as a result of the scale necessary to include the other traces on the same set of axes. A plot of the fire truck log-likelihood alone would reveal that this function is peaked at the correct azimuth and falls off smoothly as the azimuth error grows, thereby allowing for joint inference on the target type and orientation using these data. These results provide some evidence that the conditionally Gaussian model may be more appropriate for application to algorithms for joint tracking and recognition using HRR data. In Section V we investigate this possibility further by testing each model in a simulation of joint tracking and recognition.
Fig. 4. Comparison of log-likelihood functions using simulated L-band and X-band HRR data. Range-profile for fire truck at 19.95 deg azimuth selected as observation, log-likelihoods under each model computed for each vehicle for azimuth angles from 10 to 30 deg. In all panels, solid line shows log-likelihood for correct vehicle, the fire truck.

As discussed in Section IVB, one criterion for selecting sizes of the orientation bins for the conditionally Gaussian model is that the likelihood of any range-profile should be approximately constant over the bin. However, if we chose bin sizes such that the deterministic model log-likelihood were constant, the resulting bins would be exceedingly small. Physical reasoning leads us to conclude that the first nulls on either side of the true azimuth result from phase cancellation of some of the large peaks. Therefore, we have chosen our bin sizes to be several times larger than the mainlobe of the deterministic log-likelihood function. The variation of performance as a function of the bin size is an area of ongoing research.

V. SIMULATION RESULTS

Two simulations are described that test the potential of our methodology using simulated HRR data. In each case, we have made assumptions to simplify the problem being addressed from the general ATR problem presented earlier to allow us to focus on specific issues relating to HRR data.

A. Joint Orientation Estimation and Recognition for a Closing Aircraft Target

In our first ATR simulation, an unknown aircraft target is encountered by an airborne sensor platform at long range. It is assumed that detection and tracking of the position of this target are performed by an external system. A sequence of simulated range-profiles is observed as the target moves relative to the sensor. The goal is to estimate the target orientation during each simulated illumination and to determine the target type. Thus, the target trajectory is an element of the space

$$\text{SO}(3)^K \times A.$$  \hfill (16)

The target type is constrained to be either the F-117 or X-29 aircraft. The target and sensor follow
straight-line flight paths at constant velocities and maintain roll angles of 0 deg (level flight) during the encounter. These assumptions imply that the orientation of the target is completely specified by its yaw and pitch angles relative to the sensor. We further assume that the yaw and pitch angles lie between ±10 deg during the encounter. The focus here is on the simulated range-profiles and their utility in estimating orientation and identifying targets. Thus, other factors such as aircraft dynamics have been greatly simplified. The limited extent of possible aircraft orientations allows for development of a library of range-profiles computed on a fine grid in orientation, while keeping the total size of the library reasonable.

We have developed an estimation algorithm to operate under this scenario. We thank Mohammad Faisal for his assistance in developing the simulation presented here. Libraries of range-profiles for the F-117 and X-29 aircraft were simulated via XPATCH. The yaw angle was sampled uniformly at 0.2 deg intervals, and the pitch angle was sampled at a yaw-dependent interval chosen to keep the arc length on the unit sphere between neighboring pitches approximately 0.2 deg.

Values were chosen for the initial position, initial orientation, and velocity of the target, and were used to compute a sequence of true orientation states for the target during the simulation. A true target type was chosen, and XPATCH was used to simulate the sequence of observed range-profiles corresponding to the sequence of true orientations. Thus, the libraries and observations used here were computed independently.

In this simulation, we estimate orientation and target type only, and we have therefore chosen a very simple dynamical model to relate past and present orientation estimates; namely, that the yaw and pitch angles defining the aircraft orientation vary linearly over a sliding window of W illuminations in time. Thus, a sequence of orientations over the window are completely determined by the yaw and pitch angles at the window endpoints.

The estimation algorithm proceeds as follows. After loading range-profile libraries for both aircraft and the first W observed range-profiles, initial estimates of target type and the first W orientations are generated. This is accomplished through a series of global searches through the range profile libraries to determine the target type and linear orientation sequence that maximize the joint likelihood of the first W observed range-profiles.

Future orientation estimates are generated through a local search. The window endpoints are shifted by one illumination, and initial orientation estimates at the new endpoints are found by linear interpolation from the previous estimates. The set of nearest neighbors to each endpoint estimate is found. Our grid is nearly rectangular, so that in most cases, each endpoint has four neighbors, found by incrementing or decrementing the yaw or pitch. Consider the current estimate and its neighbors as candidate orientations, so that we have 25 possible pairs of candidates, each defining an orientation sequence over the window. The joint likelihood of each sequence is evaluated, using the current target type estimate, and the maximum-likelihood candidate pair is selected as the updated estimate. This process is repeated until the new estimate is equal to the current estimate, yielding a nearby local maximum of the joint likelihood surface.

Recognition is performed during the initialization process described above, in the sense that a global search is performed through the libraries for both target types. To allow for the possibility that this search may have produced the incorrect target type, the algorithm considers the hypothesis that the alternate target type is correct, and evaluates the joint likelihood of the current orientation estimates under this hypothesis. The local search is again implemented to find a local maximum of the likelihood surface. The joint likelihood of the new orientation sequence and the alternate target type hypothesis is compared with that of the current estimates, and if the new likelihood is greater, then the target type estimate is changed to the alternate target type, and the current orientation estimates are replaced by the new sequence. This process is invoked at regular intervals defined by an integer number of illuminations.

The software implementation includes graphics routines for visualization of the data and true and estimated parameters. A single frame of graphic output illustrating the state of the algorithm immediately following the initialization procedure described above is presented in Fig. 5. In the right
Fig. 6. Results of orientation estimation for simulation 1. No initialization or recognition performed in this case. In left panel, sequences of true yaw angles and yaw estimates are plotted. Right panel shows similar plots of pitch angles.

Fig. 7. Results of joint orientation estimation and recognition for simulation 1. Both initialization and recognition performed in this case. In left panel, sequences of true yaw angles and yaw estimates plotted. Right panel shows similar plots of pitch angles.

panel, the gray curves indicate the true sequence of yaw and pitch angles assumed by the target during the simulation, while the black line segments indicate the yaw and pitch estimates for the first 32 illuminations. A sequence of 32 observed range-profiles and the library elements corresponding to the current orientation estimates are displayed in the left panel. The center panel contains a rendering of the true and estimated target types at the true and estimated orientations, for illumination number 16.

True orientation states for the simulation were generated as follows. The target begins the simulation at a range of 12.5 mi, at a yaw angle of −4 deg relative to the line-of-sight of the radar, and at a pitch angle of 4 deg. The aircraft flies along a straight line at 500 mi/h for 10 s. The orientation angles are computed at 200 sample times over the duration of this flight.

In our first test of this simulation, we provided the algorithm with the true target type and the true target orientations for the first 32 observations (the initialization procedure and recognition step were not performed). The results of this test are presented in Fig. 6. The left panel of this figure shows the sequence of true yaw angles and the resulting estimates. The estimates shown here are taken from the midpoints of the line segments defining the final estimates of the orientation sequences for each window position. The right panel shows similar plots for the pitch angles. The angle estimates appear as a staircase approximation to the smooth curve depicting the true angles, with small steps corresponding to the fine orientation grid.

In a second test of our algorithm, the initialization procedure and recognition step have been included. Results from one implementation of this test are shown in Fig. 7. As before, the left panel shows the true yaw angles and estimates, and the right panel shows the true pitch angles and estimates. It is clear from the left panel that our initialization...
procedure produced a very significant error in this case. This error is interesting in that it results from a symmetry present in our libraries, which in turn results from a physical symmetry of the aircraft. The F-117 and X-29, like most aircraft, exhibit left-right symmetry, or symmetry with respect to the x-z plane in body-centered coordinates. Thus, any such aircraft rotated through a yaw angle of $\psi$ will have the same arrangement of reflectivity versus range as when rotated through a yaw angle of $-\psi$. XPATCH produces nearly identical range-profiles at these two orientations, resulting in a symmetry in our range-profile libraries, and thereby resulting in the orientation ambiguity encountered here. Note that this ambiguity is present throughout the simulation in that the estimated yaw angle is consistently close to the negative of the true yaw angle. Such ambiguities are resolvable if tracking information is available, which is not the case here. Note that we have conducted other tests of this algorithm in which a sign error in the yaw estimate did not occur.

Recognition results for this simulation were excellent. The algorithm consistently picked the correct aircraft type during the initialization procedure. Also, each time the algorithm considered the hypothesis that the alternate target type was correct, this hypothesis was rejected. Such a result was expected in this case, as the library range-profiles for the two aircraft exhibited observable differences over the entire range of possible orientations, for example in the number and location of peaks.

This simulation has demonstrated the potential for successful joint orientation tracking and target recognition using simulated range-profile data, using the deterministic model log-likelihood (13) and a simple constant orientation rate dynamical model for the target motion. The simulation provided generally positive results for orientation tracking and very positive results for recognition in simplified ATR environment in which the target orientation is restricted to a $20 \times 20$ deg orientation window, and the target type is limited to one of two candidates. Further improvements on this simulation would include considering more candidate target types, incorporating the conditionally Gaussian model for range-profiles, and testing the performance of the algorithm when the observations include additive noise. All of these items are included in our second simulation, described in the next section.

B. Joint Orientation Tracking and Recognition of Ground Targets

The simulations presented in the previous section demonstrated the potential for jointly estimating target type and a sequence of target orientations from a sequence of simulated range-profiles. While demonstration of this potential is of interest, the simulations have not presented results quantifying the performance of the algorithm in terms of the rate of successful recognition or the accuracy of orientation estimates generated, nor has there been any consideration of the effect of additive noise on estimation performance. Also, the deterministic model for range-profiles was used exclusively, largely because these simulations were developed prior to conducting the investigation of the conditionally Gaussian model presented in Section IV. The simulation presented in this section attempts to address each of these issues. We thank Zoltan Bekker for his assistance in developing these simulations.

For these simulations, we consider joint tracking and recognition of ground vehicles from an airborne sensor platform. The data available for estimation of target orientation and recognition are sequences of simulated range-profiles drawn from the URISD, described in Section IV. The target is a rigid body that moves along flat ground in a straight line at constant velocity. The sensor platform flies in a straight line at constant velocity, and is assumed to maintain a constant elevation angle with respect to the target. An HRR sensor mounted on the platform remains pointed at the target throughout the encounter. Given these assumptions, the target orientation $\theta$ is determined solely by the azimuth angle of the target relative to the sensor, which takes its value on the circle. Thus, for this final simulation, the target trajectory is an element of the space $\mathbb{SO}(2)^K \times \mathcal{A}$. (17)

For the development of our estimation algorithm, we make the assumption as in the previous simulation that the azimuth angle varies linearly over a sliding window in time.

A particular instance of our simulation is defined by selecting one of the four vehicles (fire truck, school bus, m1 tank, t1 tank) as the true target, selecting a fixed elevation angle and frequency band for the simulation, and choosing values for the parameters governing the relative motion of the target and sensor. These parameters are used to compute the azimuth angle of the target relative to the sensor at the observation times, which are spaced at regular intervals over the duration of the simulation. The sequence of azimuths is used to draw a corresponding sequence of range-profiles from the appropriate data set in the URISD. The observations $r$ are formed as the sum of these range-profiles and a sequence of complex, Gaussian distributed pseudorandom numbers with mean 0 and variance $N_0$. The noisy observations are read from a file by our algorithm at the start of the simulation.

A database is developed for each target that characterizes the set of range-profiles for that target at a discrete sampling of the possible azimuth angles. Each database is referred to as a library. When using
the deterministic model, the libraries are created by selecting a fraction, typically one-half or one-fourth, of the range-profiles from the dataset from the URISD for each target at a fixed elevation angle and frequency band. When using the conditionally Gaussian model, the set of possible azimuth angles is divided into overlapping patches, and the libraries consist of mean range-profiles and range-bin variances computed from all of the range-profiles in each patch. The patch-size is chosen to be 3 deg for the L-band data and 1 deg for the X-band data, as discussed in Section IVD. Each patch overlaps with its neighbors by one-half of the patch size. The estimation algorithm searches through the libraries, seeking a sequence of library entries that maximize the joint likelihood for a particular sequence of observations. When using the conditionally Gaussian model, if the likelihood of observing a given range-profile is maximized by a particular azimuth patch, then the azimuth estimate is set equal to the azimuth from the center of the patch.

The estimation algorithm we have developed for these simulations is based largely on our assumption that the azimuth varies linearly over a time window of length $W$, where $W$ is an integer number of illuminations of the target. This constraint implies that a sequence of $W$ azimuth estimates is determined by the estimates at the endpoints of the window. The estimation algorithm is initiated by conducting a series of global searches through the libraries for each candidate target to determine the vehicle and the azimuths at the window endpoints that maximize the joint likelihood for the first $W$ observed range-profiles.

Future azimuth estimates are generated through a local search, as in Section VA. Also, as in the previous simulation, alternative target types are considered at regular intervals. Given that our algorithm may produce different estimates of target type over the course of a single simulation, we define correct recognition as the case where the algorithm selects the correct vehicle during the initialization process, and maintains the correct vehicle estimate throughout the simulation.

1) Simulation Results: We have implemented our algorithm for a particular encounter scenario, using both the L-band and the X-band data from the URISD, and for a range of values of the noise variance $N_0$. The scenario parameters are as follows. The target is the m1 tank model. The target begins the simulation 500 m west and 1000 m north of the sensor, with an initial azimuth angle of 220° relative to the sensor, and moves in a straight line at 17.78 m/s. The sensor moves north at 88.9 m/s maintaining a constant elevation angle of 10° between itself and the target. The sensor illuminates the target 200 times at 50 ms intervals.

Data from a typical realization of this scenario are shown in Fig. 8. The left panel shows a sequence of 20 noise-corrupted L-band range-profiles for the m1 tank model. The right panel shows a sequence of 20 library entries corresponding to our sequence of azimuth estimates at observation times. For this example, the noise variance is set to a value of 0.6 square meters. Let the signal-to-noise ratio be defined as the ratio of total signal energy to noise power. Because the energy in the signal may change drastically over the course of the simulation, the signal-to-noise ratio varies as well. The signal-to-noise ratio for the data depicted in Fig. 8 is approximately 22 dB.

The performance of our algorithm under the deterministic model for this example is shown in Fig. 9. The true sequence of azimuth angles assumed by the target appears as a smooth curve, while the sequence of estimates appears as a jagged approximation to this curve. The two traces are difficult to distinguish in the figure as a result of the high quality of the azimuth estimates generated in this case. Note that both the true vehicle type and estimated vehicle type are the m1 tank model, indicating successful recognition. The performance
shown here is typical for our algorithm when using L-band data at this noise level, in that the sequence of azimuth estimates tracks the true azimuth sequence very closely, and the vehicle is correctly recognized throughout the simulation.

2) Performance Analysis: L-Band: A more extensive examination of the performance of our algorithm was conducted by repeating this simulation 500 times using independent realizations of the pseudorandom noise sequences. Performance measures were computed over the 500 runs in terms of the fraction of runs in which correct recognition was achieved, and the Hilbert–Schmidt norm of the error in the azimuth estimates. This process was repeated for noise variances between 0.6 and 2.4 square meters, under both the deterministic model and the conditionally Gaussian model.

As developed in [19], a performance measure for estimators in which the parameter is a rotation that takes its value on $\text{SO}(2)$ or $\text{SO}(3)$ is given by the Hilbert–Schmidt norm of the difference between the true rotation matrix and the estimate. For azimuth estimation on the circle, the square of this Hilbert–Schmidt norm is equal to [7, 19]

$$4 - 4\cos(\theta_d)$$

where $\theta_d$ is the difference between the true azimuth angle and the estimate. We compute the Hilbert–Schmidt norm-squared for each azimuth estimate, and this performance measure is averaged over the number of estimates generated in each simulation run and over the 500 runs at each noise level to generate an estimate of the expected estimation error.

The results of these simulations for L-band data are shown in Fig. 10. In the left panel of the figure, the Hilbert–Schmidt norm-squared on azimuth estimation error is plotted as a function of the noise variance. The center panel shows the fraction of simulation runs in which correct recognition was achieved. The right panel shows the angular estimation error for the case where the correct vehicle type is assumed known. In each panel, the solid line indicates the performance under the deterministic model, and the dashed line indicates the performance under the conditionally Gaussian model.

The figure indicates generally good recognition performance, in that the algorithm achieved correct recognition better than 90 percent of the time for noise variances up to 1.4 square meters, and better than 70 percent correct recognition for all noise variances, under either model. Also, the Hilbert–Schmidt norm-squared on the angular estimation error is consistently less than 1.4. To interpret this result, consider that the Hilbert–Schmidt bound for the worst case estimator has a value of 4. If we assume that the targets are physically asymmetric objects, then the worst case estimator randomly selects the azimuth estimate with uniform probability density over the circle.

For this simulation, the performance under the conditionally Gaussian model is approximately equivalent to that under the deterministic model. Such performance is achieved by the Gaussian
model while using considerably smaller libraries. For L-band data, the deterministic model libraries each contain 1200 complex-valued range-profiles, whereas the Gaussian model libraries contain 240 complex-valued mean range-profiles and real-valued range bin variances. Thus the total size of the L-band libraries for the Gaussian model is smaller than those for the deterministic model by a factor of $3^\frac{1}{2}$.

It must be noted that the performance of our algorithm is critically dependent on the choice of the size of the sliding window over which the linear azimuth dynamical model is enforced. For optimal recognition performance in the presence of noise, longer windows are desired. For the deterministic model, the log-likelihood for a sequence of observations is given by the sum of the individual log-likelihoods. Therefore, if the azimuth estimates are accurate, the use of longer windows increases the log-likelihood margin between the correct target and all other targets. However, because the true azimuth sequence is not linear, the use of longer windows increases the azimuth estimation error over the length of the window. This establishes a fundamental performance trade-off for the choice of this parameter. The results presented above were obtained after trial-and-error suggested a window length of 20 observations provided the best performance when using the L-band data. This issue may be avoided altogether by using a more accurate model for target dynamics.

3) Performance Analysis: X-Band: The simulations described above were repeated for identical scenario parameters using the X-band data from the URISE. The simulations were run 500 times at noise variances between 0.6 and 12.4 square meters. The recognition rates and Hilbert–Schmidt norms on the azimuth estimation errors were computed as before. The results of these simulations are shown in Fig. 11. It is clear from the figure that the performance of the algorithm under the deterministic model suffered greatly when using X-band data. The left panel indicates that the azimuth estimation error exceeded the Hilbert–Schmidt bound for the worst case estimator at all noise variances tested. The center panel shows that correct recognition was never achieved for more than ten out of the 500 runs at any noise variance. Recall that correct recognition is achieved only when the algorithm produces the correct vehicle estimate throughout the entire simulation. In contrast, the right panel indicates good performance in terms of azimuth estimation error at all noise levels, when the correct target type was assumed known. This performance can be understood by examining the upper right panel of Fig. 4. The width of the central peak in the log-likelihood function is less than 0.1 deg, and outside of this peak the log-likelihood for an incorrect target is larger than that for the correct target. Thus, if the algorithm makes even a small error in the azimuth estimate, it will change the target type estimate, resulting in incorrect recognition.

It is also clear from the figure that the performance using X-band data was significantly improved under the conditionally Gaussian model. A recognition rate of better than 70 percent was achieved, and the Hilbert–Schmidt norm-squared on the azimuth estimation error was consistently less than 1, for noise variances up to 7 square meters. This improved performance was achieved at a considerable savings in memory requirements over the deterministic model. The total size of the X-band data libraries for the conditionally Gaussian model is smaller than those for the deterministic model by a factor of more than 16. Note that the accuracy of azimuth estimates seen in Fig. 11 is not inconsistent with Fig. 4, since the log-likelihood is still sensitive to target orientation, as discussed following Fig. 4. Also, note that having some robustness to target orientation is crucial to being able to track and recognize a maneuvering target. There is a trade-off between robustness to uncertainty in target orientation and estimation accuracy of target orientation that must be explored in future work.

VI. CONCLUSIONS AND FUTURE WORK

A methodology for automatic tracking and recognition of targets based on jump-diffusion
processes has been extended to incorporate observations from an HRR. The critically important task of orientation estimation is performed by following the gradient of the joint likelihood surface for a sequence of HRR range-profiles. This methodology is flexible enough to accommodate a variety of models for HRR data, and indeed different models for the same target may be used in different frequency bands. We have shown how the proposed methodology does yield reasonable results for the deterministic and stochastic models for range-profiles proposed in this paper. These two models represent extreme points within the family of Gaussian models. Initial results presented in this paper indicate that the stochastic model may be more appropriate for ATR in the face of uncertainty about the target orientation. Intermediate models that incorporate some correlation and some variation are currently being explored. Future work will incorporate models for and data from multiple polarization channels for enhanced recognition performance.

We presented simulations designed to illustrate the potential for joint tracking and recognition using simulated HRR range-profiles. In every simulation scenario that we have examined, we have achieved general success. The implication is that joint tracking and recognition from simulated range-profiles is possible, given an appropriate model for the sensor data in the form of a likelihood function, data libraries that characterize the range-profiles expected from a given target at the possible orientations, and an appropriate model for the target motion. Our simulations suggest that the conditionally Gaussian model provides improved performance over the deterministic model, especially at high frequencies, with much smaller model libraries.

Future simulations testing recognition could build on these efforts in many important ways. Of primary interest is adaptation of the simulations to operate on real HRR data. This would require a coordinated effort to obtain range-profiles for which ground truth values for the target shape and reflectivity, and the target orientations at the illumination times, are known. We are currently working with personnel in the radar community to obtain data for such a test. Also required would be libraries of simulated data for use with the conditionally Gaussian model. This, in turn, requires a verification of the range-profiles produced by simulators such as XPATCH.

Other factors that will be important to include in future ATR simulations are an extension to full polarimetric HRR data and inclusion of models with articulating parts. Finally, and most importantly, will be the incorporation of the HRR processing used in these simulations into systems for joint detection, tracking and recognition of multiple targets where high resolution radar is only one of the high resolution sensors available [13].

ACKNOWLEDGMENTS

Technical interactions with Michael I. Miller, Donald L. Snyder, and Anuj Srivastava contributed significantly to the work reported here. Vincent Vannicola at USAF Rome Laboratory provided us the HRR data and was helpful in technical discussions. We thank Anuj Srivastava, Mohammad Faisal, and Zoltan Bekker for their assistance in developing the simulations presented herein. Dennis Andersh at USAF Wright Laboratory provided a copy of the XPATCH HRR simulator, and the USAF Office of Scientific Research provided us a copy of the University Research Initiative Synthetic Dataset.

REFERENCES

Non-cooperative target recognition using the adaptive Gaussian classifier.

Comparison of two target classification techniques.

Variability of ultra-high range resolution radar profiles and some implications for target recognition.
SPIE, 1699 (1992), 256–266.


General Pattern Theory.

Representations of knowledge in complex scenes.

Hilbert–Schmidt lower bounds for estimators on matrix lie groups.

Automatic target recognition using high resolution radar range-profiles.

High resolution radar models for joint tracking and recognition.

Low-frequency approach to target identification.

Application of sequence comparison methods to multisensor data fusion and target recognition.
Application of sequence comparison techniques to
multisensor data fusion and target recognition.
In Proceedings of the 32nd Conference on Decision and

D. L. (1997)
Automatic target recognition organized via jump-diffusion
algorithms.
IEEE Transactions on Image Processing (Special Issue on
Automatic Target Detection and Recognition), 6, 1 (Jan.

Conditional-mean estimation via jump-diffusion processes
in multiple target tracking/recognition.
IEEE Transactions on Signal Processing, 43, 11 (Nov.
1995), 2678–2690.

Overview of high range resolution radar target
identification.

Correlation scales of laser speckle in heterodyne
detection.

Introduction to Radar Systems (2nd ed.).

Radar target identification.

Inferences on transformation groups generating patterns
on rigid motions.
Ph.D. thesis, Washington University, Saint Louis, MO,
July 1996.

Multiple target direction of arrival tracking.
IEEE Transactions on Signal Processing, 43, 5 (May

Target recognition and detection sensitivity in
two-dimensional microwave imaging.
Technical report VPRC-2-90, RADC/OCD Griffiss

Detection, Estimation and Modulation Theory, Vol. 3.

Detection, Estimation and Modulation Theory, Vol. 3.

Coherent averaging of range profiles.
In Record of the IEEE 1995 International Radar
Conference, Alexandria, VA, May 1995, 456–461 and
794.

Radar target classification of commercial aircraft.
IEEE Transactions on Aerospace and Electronic Systems,

Steven P. Jacobs (S’95—M’96) was born on November 18, 1966 in Chicago,
IL. He received the B.S., M.S., and D.Sc. degrees in electrical engineering from
Washington University, St. Louis, MO, in 1987, 1990, and 1997, respectively.
Since 1997, he has been a Visiting Assistant Professor in the Department of
Electrical Engineering at the University of Pittsburgh. His focus is on
undergraduate education, particularly in the area of analog and digital
communication systems.
Dr. Jacobs is a member of Eta Kappa Nu and Tau Beta Pi.
Joseph A. O'Sullivan (S'83—M'86—SM'92) was born in St. Louis, MO, on January 7, 1960. He received the B.S., M.S., and Ph.D. all in electrical engineering from the University of Notre Dame, Notre Dame, IN, in 1982, 1984, and 1986, respectively.

In 1986, he joined the faculty in the Department of Electrical Engineering at Washington University, St. Louis, MO, where he is now an Associate Professor. He has joint appointments in the Department of Radiology and the Department of Biomedical Engineering. He is Director of the Electronic Systems and Signals Research Laboratory. He is a member of the Magnetics and Information Science Center and the Center for Imaging Science at Washington University. He is a consultant for and on the Board of Directors of Abacus Controls, Inc. His research interests include information theoretic imaging, estimation theory, alternating minimization algorithms, tomographic imaging, object recognition, and magnetic recording.

Dr. O’Sullivan was Secretary of the Faculty Senate, Secretary of the Senate Council, and Faculty Representative to the Board of Trustees at Washington University from 1995 to 1998. He was the Publications Editor for the IEEE Transactions on Information Theory from 1992 to 1995, is currently Associate Editor for Detection and Estimation, and is a Guest Associate Editor for the Special Issue on Information Theoretic Imaging. He was cochair of the 1999 Information Theory Workshop on Detection, Estimation, Classification, and Imaging, and was in charge of travel grants and registration for the 1995 Information Theory Workshop on Information Theory, Multiple Access, and Queueing. Prof. O’Sullivan is active in local IEEE activities as well, including being chair of the St. Louis Section of the IEEE in 1994. He is a member of Eta Kappa Nu and SPIE.