Automatic Target Recognition via the Simulation of Infrared Scenes

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ABSTRACT

Many FLIR simulation efforts have been undertaken with the goals of training and testing automatic target recognition algorithms and predicting performance. In our pattern theoretic Grenander/Bayesian approach to the ATR problem, simulation provides the heart of the ATR algorithm itself. An hypothesized scene, simulated from the emissive characteristics of the hypothesized scene elements, is compared with the collected data by a likelihood function based on sensor statistics. This likelihood is combined with a prior distribution defined over the set of possible scenes to form a posterior distribution. Jump-diffusion processes which sample from the posterior provide the engine of the inference algorithm. New objects are detected and object types are recognized through discrete jump moves. Between jumps, the location and orientation of objects are estimated via continuous diffusions.

Both the diffusion and jump operations involve the simulation of scenes produced by hypothesized configurations. The radiant intensities of ground vehicles are simulated with Keweenaw Research Center’s PRISM code. Rendering the scene is most effectively accomplished by pipelined rendering engines such as Silicon Graphics. We demonstrate the execution of our algorithm on a Silicon Graphics Onyx/Reality Engine.

1 INTRODUCTION

Automatic target recognition (ATR) systems may encounter a wide spectrum of scenarios, characterized by three fundamental difficulties: 1) Geometric variability; Targets may take on different appearances depending on the orientations and positions of the object; 2) Image variability: The data obtained may vary with environmental conditions and will be subject to the noise characteristics of the sensor. In addition, the textures comprising a scene will have randomness associated with them since it is not feasible to specify every minute aspect of a scene; 3) Complexity/scene variability: The number of targets encountered will not be known in advance, and targets may enter or leave the scene at random times. The development of ATR systems invariant to all three kinds of variability depends upon a framework for the understanding and representation of complex real and natural scenes. Grenander’s general pattern theory [1, 2] offers this essential infrastructure for the representation and inference of structures in complex systems [3].

Although this work focuses on the development of a pattern theoretic algorithm for a forward-looking infrared sensor mounted on an airborne platform [4, 5, 6], the principles employed are not particular to FLIR sensors. To illustrate the generality of our framework, we also present a model for a LADAR sensor which may be used instead of or in addition to our FLIR model.

1.1 Pattern Theory for ATR

Tremendous effort has gone into the development of ATR algorithms. The more sophisticated “model-based” systems classify based on CAD-like models [7, 8]. Traditional algorithms maintain a conceptual separation between “low-level” vision (edge detection, segmentation, etc.) and higher levels of inference (classification.)

Our “top-down” pattern theoretic philosophy represents a dramatic departure from traditional machine vision al-
algorithms. Instead of performing separate steps of segmentation, feature extraction, etc., our approach estimates the configuration of targets directly from the measured data. Patterns, such as those known by an automatic target recognition system, are represented as templates. These templates are subjected to transformations forming mathematical groups, and the transformations which yield a best match to the measured data are chosen as the solution. Thus, our ability to recognize pattern depends directly on our ability to synthesize those patterns. Our work has been guided by this paradigm of recognition through simulation.

We take a Bayesian approach in which a hypothesized scene, simulated from the emissive characteristics of the hypothesized scene elements, is compared with the collected data by a likelihood function based on sensor statistics. Thus, simulation technology is central to our work in two distinct ways: 1) as in any ATR program, it provides synthetic data sets for algorithm evaluation, and 2) simulation provides the heart of the ATR algorithm itself. The likelihood is combined with a prior distribution defined over the set of possible scenes to form a posterior distribution. Since the number of objects in the scene (the model order) is not known in advance, we must define a single posterior probability across all of the model subspaces.

In the realm of FLIR and visual images, our maxim of pattern recognition = pattern synthesis may be formulated as computer vision = computer graphics, an idea championed by Gagalowicz[9] and employed by Talluri and Aggarwal for autonomous navigation[10].

1.2 Inference via Jump-Diffusions

Our applications possess discrete and continuous aspects. The sensor will be presented with an unknown number of targets. In addition, the targets themselves will likely be members of some small set of vehicles. These parameters are discrete in nature. The positions and orientations of targets are inherently continuous in nature.

We have built the logical and computational engines of our deduction algorithms around jump-diffusion processes which provide the dynamic flexibility to accommodate higher and lower complexity scenes [3, 11, 12]. Jump-diffusions are inherently discrete and continuous in the nature of their search, and therefore accommodate the very different continuous and discrete nature of image understanding. The jumps deal with changes of target type and number and the diffusions [13] accommodate the continuous parameters. Technically, jump-

Figure 1: Top-down view of a configuration of targets.

diffusion algorithms permit sampling from complex posterior distributions which would otherwise be difficult or impossible to simulate directly.

2 THE BAYESIAN MODELS

Figure 1 illustrates a top-down representation of a particular configuration of ground-based targets. Sensors such as imaging laser radars and visual and infrared cameras observe the scene through the effects of obscuration and perspective projection, in which a point $(x,y,z)$ in 3-D space is projected onto the 2-D detector according to $(x,y,z) \mapsto (x/z,y/z)$, as shown in Figure 2. This creates the vanishing point effect in which objects which are further away from the sensor appear closer to the center of the detector. Objects will appear skewed in different ways depending on where they appear in the image plane.

2.1 Infrared (FLIR) Model

FLIR cameras passively sense objects via the infrared radiation they emit or reflect. In the bands we are concerned with, particularly the 8-12 micron band, emitted radiation is the dominant effect. The radiation emitted depends upon the thermodynamic state of the object and its emissivity properties. Atmospheric absorption attenuates the radiation reaching the sensor. We will ignore
such absorption effects here, although they could easily be incorporated in the model.

For now, we will assume the Earth is a flat surface of constant known intensity on the x-z plane extending infinitely in all directions. We will also assume that the sky radiates a constant known intensity. We plan to relax these assumptions in future work.

We currently assume that target facets radiate known intensities. The intensities may be determined from measured data [14], simulation (such as PRISM [15] or GT-SIG [16]), or a combination of the two [17]. In these simulations we employ radiances predicted by the PRISM (Physically Reasonable Infrared Signature Model) software [15] developed by Michigan Technological University’s Keweenaw Research Center (data courtesy Dr. A. Curran, Michigan Tech/KRC) under the direction of TACOM. Wireframe models and associated radiance images of some orthogonal “draftsman” views of the M2, the M60, and the T62 are shown in Figure 3.

Unfortunately, real FLIR sensors are subject to various sources of error. We will invoke the CCD camera model of Snyder, Hammoud, and White [18]. The camera introduces blurring according to

\[ \mu(y) = \sum_{p \in P} q(y|p) \lambda^{IR}(p), \]

where \( \lambda^{IR}(p) \) is the ideal observed intensity and \( q(y|p) \) is the camera point spread function, normalized so that \( \sum_{y \in \mathcal{Y}} q(y|p) = 1 \). For simplicity, we disregard background counts, readout noise, nonuniform response, and wavelength dependency in the camera, but these distortions could be accommodated readily.

Figure 4 shows an ideal infrared scene \( \lambda^{IR} \) corresponding to Figure 2. We have embedded the PRISM models in a real infrared image. Here, the real infrared background does not match the perspective of the object models; the real image is only intended to provide a reasonable desert background texture. Figure 5 shows the corresponding \( \mu \), this ideal infrared scene \( \lambda^{IR} \) blurred with a Gaussian point-spread function \( q \).

The data \( D^{IR}(y) \) collected by a CCD camera is Poisson distributed with mean \( \mu(y) \). A sample of Figure 4 with Poisson noise is shown in Figure 6. The Poisson loglikelihood of the data \( D^{IR} \) given \( \lambda^{IR} \) is

\[ L^{IR}(D^{IR}|\lambda^{IR}) = -\sum_{y \in \mathcal{Y}} \mu(y) + \sum_{y \in \mathcal{Y}} \ln[\mu(y)]D^{IR}(y). \]

Given an estimated configuration \( x \) and a series of images \( D^{IR}_k \) collected at discrete times \( \kappa = 0 \ldots \kappa_T \), where \( \kappa_T \) is the current time, we can write

\[ L^{IR}_{\kappa_T}(D^{IR}|x) = \sum_{\kappa=0}^{\kappa_T} L^{IR}(D^{IR}_k|\text{render}^{IR}(x)), \]

where \( \text{render}^{IR}(x) \) represents the operation of rendering, via perspective projection and obscuration, the radiant intensities of the objects in the configuration and the

Figure 2: Wireframes of targets viewed under perspective projection and obscuration.

Figure 3: Orthogonal views of faceted models of an M2 (top), an M60 (middle), and a T62 (right). Wireframes are shown on the left, associated PRISM radiances on the right. Courtesy Dr. A. Curran, Keweenaw Research Center, Michigan Technological University.
background onto the image plane. Note that this rendering process (which we have implemented on the Silicon Graphics) may be quite intricate; thus, the loglikelihood is a highly nonlinear, extremely complicated function of the configuration parameters.

Real FLIR images will also contain manufacturing artifacts such as dead and saturated pixels. We have randomly placed such artifacts uniformly across the image in Figure 6 to make Figure 7. This is the data that our algorithm processes in Section 4. Although the likelihood model used here does not explicitly incorporate these artifacts, they have little effect on the performance of the algorithm.

2.2 Laser Radar (LADAR) Model

Here we will explore a model for laser radar range data. Intensity and Doppler information, if available, can be incorporated similarly.

Let $\lambda^{LR}(y)$ be the true distance from the sensor to the scene at pixel $y$. We will employ Shapiro’s model for laser radar range images [19, 20, 21], with a few changes to suit our purposes. In particular, we will explicitly incorporate the ambiguity inherent in the range measurements, so the measurements are more accurately characterized as taking values on the torus rather than the real line. Although a wrapped Gaussian or Von Mises density would be more appropriate for toroidal data, we will employ Shapiro’s original Gaussian density as a reasonable approximation. The loglikelihood of collecting range data $D^{LR}$ given true range $\lambda^{LR}$ is then

$$L^{LR}(D^{LR}|\lambda^{LR}) = \sum_{y \in Y} \left\{ \ln \left( \frac{Pr_A(y)}{\Delta R} \right) + [1 - Pr_A(y)] \times \right.$$

$$\exp \left\{ - \frac{(D^{LR}(y) - [\lambda^{LR}(y) \mod \Delta R])^2}{2\delta(y)^2} \right\} \right\} \right.$$ (5)

where $\Delta R$ is the extent of the range uncertainty interval and $\delta(y)$ and $Pr_A(y)$ are the local range accuracy and probability of anomalous measurement for pixel $y$ given by $\delta(y) = R_{res}/\sqrt{CNR(y)}$ and $Pr_A(y) = \left[ \ln(N) - 1/N + 0.577/\sqrt{CNR(y)} \right]$, where $N = \Delta R/R_{res}$, $R_{res}$ is the range resolution, and $CNR$ is the carrier-to-noise ratio taken to be $CNR(y) = \Xi \exp \left\{ -2\alpha \lambda^{LR}(y) / [\lambda^{LR}(y)]^2 \right\}$, where $\alpha$ is the atmospheric extinction coefficient and $\Xi$ is a constant derived from the properties of the laser radar. Notice that the probability of anomaly $Pr_A(y)$ and the local range accuracy $\delta(y)$ increase with hypothesized distance $\lambda^{LR}(y)$.

Figure 8 presents an example of a noiseless range image (with ambiguity) corresponding to Figure 2. A sample of this image corrupted with anomalous pixels and range-dependent measurement error is shown in Figure 8.

Given an estimated configuration $x$ and a series of images $D^{LR}_\kappa$ collected at discrete times $\kappa = 0 \ldots \kappa_T$, where $\kappa_T$
is the current time, we can write
\[
L_{\kappa T}^{LR}(D_{\kappa T}^{LR} | \text{render}^{LR}(x)) = \sum_{\kappa=0}^{\kappa_T} L_{\kappa T}^{LR}(D_{\kappa T}^{LR} | \text{render}^{LR}(x)),
\]
where \(\text{render}^{LR}(x)\) represents the operation of rendering, via perspective projection and obscuration, the range to elements of the scene.

Many computer graphics engines, including the Silicon Graphics hardware, account for obscuration with a z-buffer algorithm. As object pixels are rendered, their distance is stored in a pixel-registered z-buffer. New pixels are only written to the rendered image if their distance is less than what is currently stored in the z-buffer. After the scene is fully rendered, the final contents of the z-buffer provide ranges as a by-product of the rendering algorithm. Thus, in simulating infrared images \(\lambda^{IR}\), we can essentially get simulated range images \(\lambda^{LR}\) “for free.”

2.3 Posterior Distribution

To fuse data from different modalities, we simply add their loglikelihoods, e.g., \(L = L^{IR} + L^{LR}\).

For a prior, we assume a uniform distribution on target types and orientations and a uniform distribution with finite support on target positions. Ideally, the prior should incorporate the fact that two targets cannot occupy the same physical space. However, we have currently found explicit implementation of such a prior to be unnecessary. When hypothesizing new targets, we just make sure the new target does not fall too close to an existing target.

The likelihood and prior combine to form a posterior density in Gibbs form
\[
\pi_{\kappa T}(x|D) \propto \exp[H_{\kappa T}(x|D)]
\]
where \(P_{\kappa T}(x)\) is the logprior and \(H_{\kappa T}(x|D) = L_{\kappa T}(D|x) + P_{\kappa T}(x)\) is the logposterior. Note that the posterior distribution changes with time as we collect more data. Since computational and storage requirements grow rapidly as we collect more and more data, in practice we will only retain a few of the most recently collected data frames in memory.

We sample from (7) by simulating a random process as described in the next section.

3 INFERENCE ALGORITHM

3.1 Diffusion Process

Since the diffusion process cannot change the number of targets or target types, we will have a family of diffusion processes to jump between. Each diffusion process in this
family is a stochastic gradient ascent which samples from an associated posterior distribution. The different diffusion processes correspond to different numbers of targets and different target types. Consider the composite parameter vector for an $N$-target configuration with fixed target classes at time $\kappa_T$

$$X_N = (x(1), x(2), \ldots, x(N)) \in X_N. \quad (8)$$

For the ground based targets of interest here, we represent the targets with a position on the plane and an orientation about the y-axis, so let $X_N = [\mathbb{R}^2 \times [0,2\pi)]^N$.

Our approach is to formulate a diffusion process $X_N(\tau)$ which has the property that the distribution of $X_N(\tau)$ converges in variation norm to $\pi(X_N|D) \propto \exp H(X_N|D)$, the posterior distribution for the parameter space space $X_N$. Using a discretization with a sufficiently small step size, we simulate the diffusion process defined by the Langevin stochastic differential equation

$$dX_N(\tau) = \nabla_{X_N} H(X_N(\tau)|D)d\tau + \sqrt{2}dW_N(\tau), \quad (9)$$

where $W_N(\tau)$ is a Weiner process in $X_N$, and $H(X_N|D)$ is the log-posterior associated with the parameter vector $X_N$. For the orientation parameter, additions are taken modulo $2\pi$. The “algorithmic time” $\tau$ should not be confused with the real-world time $\kappa$ over which the data is gathered.

3.2 Jump Process

Jumps allow the inference algorithm to visit subspaces with different numbers of targets and different target types. This accommodates the discrete nature of the problem. We employ three types of simples: births, to hypothesize new targets; deaths, to remove target hypotheses not well supported by the data; and metamorphs, to change hypothesized target type.

A variety of jump-diffusion processes may be formulated, all of which will result in the desired invariant measure.

The different schemes correspond to different choices of the jump intensity $q(x,dy)$. Let $T^1(x)$ be the set of states which may be reached from state $x$ in one jump move. Here, $T^1(x) = T^b_0(x) \cup T^d_0(x) \cup T^m_0(x)$, where the $T^b_0(x)$, $T^d_0(x)$, $T^m_0(x)$ represent the set of states which may be reached from $x$ via a birth, a death, and a metamorph. Similarly, define $T^{-1}(x)$ to be the set of states which may reach $x$ in one jump move.

The jumps occur at exponentially distributed times. Given a set of times $w_1, w_2, \ldots$, independent and exponentially distributed, the jump times $\tau_1, \tau_2, \ldots$ are given by

$$\tau_i = \inf \{ \tau : \int_{\tau_{i-1}}^{\tau} q(X(\tau'))d\tau' \geq w_i \}, \quad (10)$$
where \( q(x) = \int_{\mathcal{Y}(x)} q(x, dy) \). Between jumps, the process satisfies the stochastic differential equation (9) appropriate for that subspace. At each jump, the process moves from state \( x \) to a new state \( y \) according to the jump transition probability measure \( Q(x, dy) = q(x, dy)/q(x) \).

In order to achieve the desired ergodic property, we choose the jump intensities so that

1. The jump moves are reversible, i.e., \( \mathcal{T}^1(x) = \mathcal{T}^{-1}(x) \),
2. The family of jump moves are rich enough to permit any subspace to be reached from any other disconnected subspace in a finite number of jump moves,
3. \( q(x) \) and \( Q(x, dy) \) are bounded continuous functions, and
4. The jump intensities satisfy the detailed balance condition

\[
q(x)\pi(x)dx = \int_{\mathcal{T}^{-1}(x)} q(y, dx)\pi(y)dy.
\] (11)

Then, according to Theorems 1 and 2 from [3], the jump-diffusion process described above possesses the desired unique invariant measure. The exact hypotheses required for convergence are quite intricate and may be found in [22, 23, 3].

We will choose a jumping scheme analogous to the Metropolis-Hastings sampling algorithm [24, 25, 26]. At exponentially distributed times, with fixed mean \( \lambda_{\text{jump}} \), we draw a candidate \( x_{\text{prop}} \) from a proposal density \( r(x_{\text{old}}, x_{\text{prop}}) \) and compute the acceptance probability

\[
\alpha(x_{\text{old}}, x_{\text{prop}}) = \min\left\{ \frac{\pi(x_{\text{prop}})r(x_{\text{prop}}, x_{\text{old}})}{\pi(x_{\text{old}})r(x_{\text{old}}, x_{\text{prop}})}, 1 \right\}. \] (12)

The proposal is accepted with probability \( \alpha(x_{\text{old}}, x_{\text{prop}}) \) and rejected with probability \( 1 - \alpha(x_{\text{old}}, x_{\text{prop}}) \). A wide variety of proposal densities may be used; we merely require that \( r(x_{\text{old}}, x_{\text{prop}}) > 0 \) for \( x_{\text{prop}} \in \mathcal{T}^1(x_{\text{old}}) \) and \( r(x_{\text{old}}, x_{\text{prop}}) = 0 \) for \( x_{\text{prop}} \not\in \mathcal{T}^1(x_{\text{old}}) \).

This scheme corresponds to choosing the jump intensity

\[
q(x, dy) = \min\left\{ \frac{\pi(y)r(y, x)}{\pi(x)r(x, y)}, 1 \right\}r(x, y)dy. \] (13)

In this study, we choose a proposal density which proposes a birth, metamorph, or death move according to the prior on the number of targets and draws the proposal from the posterior density over the space which can be reached via the proposed move type. Further details are given in [4].

4 EXAMPLES

4.1 FLIR Data

We have implemented a jump-diffusion algorithm for FLIR on a Silicon Graphics Onyx/Reality Engine. Implementation details may be found in [4, 6]. Figure 10 shows interesting states of a sample path of the process running on the data shown in Figure 7.

Since we started the process with an empty configuration, the algorithm tries a birth on the first iteration. The M60 on the right appears larger than the other targets since it is closer to the sensor. The algorithm finds it first since it can “explain” the largest amount of data pixels with it. In iteration 3, it mistakes the T62 for an M60. It does this since it hasn’t yet found the adjacent M2 and is trying to explain some of the M2’s pixels using the barrel of the M60. This demonstrates the importance of moves which allow changes of type. In iteration 24, the algorithm finds the M2, but the hypothesis is facing the wrong direction. While the diffusions may refine orientation estimates, they are impractical for making large orientation changes, suggesting the necessity of a jump move for making such drastic changes in orientation. Notice the diffusions have found the correct placement of the M60. The remaining M60 is found in iteration 32. The algorithm continues to propose birth moves which are rejected since the data does not support a fifth target.

In iteration 34, the barrel of the incorrectly-guessed M60 is no longer needed to explain the M2 pixels, so a metamorph move swings the hypothesis around, but still incorrectly supposes it to be an M60. It is flipped back the other direction and incorrectly supposed to be an M2 in iteration 68.

Between iterations 68 and 87, the diffusions pull the incorrectly-hypothesized M2 closer to the correct position, so a metamorph move in iteration 88 correctly changes its type to a T62. The correct orientation of the true M2 is found in iteration 103. The configuration (all of the types, positions, and orientations) has been correctly deduced by iteration 117. All throughout the inference, the algorithm proposes death moves which are rejected.

4.2 LADAR Range Data

We have recently tried modifying the algorithm described above to incorporate the LADAR range model instead of the FLIR model. Interesting snapshots of a sample path
analyzing the data in Figure 9 are shown in Figure 11. Notice that, in this preliminary experiment, the algorithm incorrectly estimates the orientation of the M2.

5 DIRECTIONS FOR FUTURE WORK

Throughout this study, we have assumed that target facets radiate known intensities. In general, we can not expect facet intensities to be exactly known, since the target may radiate a range of intensities depending on operating and environmental conditions. Traditional approaches to ATR attempt to extract features which are invariant to such changes in intensity. In our context, we would summarize the target’s thermodynamic state with a parsimonious set of variables. In one view, these are nuisance parameters which should be averaged out. From our point of view, these parameters might provide useful information about the object (for instance, whether a tank has been idling or running at top speed all day.)

Land-based vehicles are just a small subset of the types of objects a FLIR sensor will encounter. We intend to expand our framework to incorporate more complex man-made objects such as buildings, roads, and runways, as well as natural ones such as lakes. Although in one sense these are nuisance parameters, in another sense they could help identify the man-made structures we are interested in, because we could enrich the knowledge representations to encapsulate such notions as “the jeep is in the lake” and “the submarine is on the runway.” The prior could aid recognition by realizing that neither of those two statements is a likely possibility. Incorporating hills, mountains, valleys, and other such geographical structures will involve relaxing the assumption that the earth is a flat surface.

Compared to the emissive characteristics of man-made structures, the emissive characteristics of natural backgrounds [27] are not well understood [28]. More complex models for the ground, perhaps incorporating Markov random field texture models, could be employed. Markov random fields have proven beneficial [29, 30, 31] for texture analysis in the segmentation of electron micrographs [23, 3]. In addition to algorithms for model-based image segmentation, algorithms have been developed which postulate appropriate models from training data using Rissanen’s minimum description length criterion [32, 33, 34]. The analysis of textures in infrared images will be especially challenging since the apparent textures change with distance from the detector.

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References


Figure 10: Iterations 1, 3, 24, 32, 34, 68, 87, 88, 103, and 117 of a jump-diffusion process for FLIR data.

Figure 11: Iterations 1, 3, 11, 12, 24, 32, 38, and 130 of a jump-diffusion process for LADAR range data.