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Laura Hicks Weir

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dBTASMTM ROBUSTNESS STUDY

by

LAURA HICKS WEIR

A THESIS

Submitted in partial fulfillment of the requirements for the degree of Master of Science in Engineering in The Department of Electrical and Computer Engineering to The School of Graduate Studies of The University of Alabama in Huntsville

HUNTSVILLE, ALABAMA

2015
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THESIS APPROVAL FORM

Submitted by Laura Hicks Weir in partial fulfillment of the requirements for the degree of Master of Science in Engineering in Electrical Engineering and accepted on behalf of the Faculty of the School of Graduate Studies by the thesis committee.

We, the undersigned members of the Graduate Faculty of The University of Alabama in Huntsville, certify that we have advised and/or supervised the candidate of the work described in this thesis. We further certify that we have reviewed the thesis manuscript and approve it in partial fulfillment of the requirements for the degree of Master of Science in Engineering in Electrical Engineering.

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Effective, radar-based, missile defense requires an efficient, accurate determination of whether an object is lethal or non-lethal. An ideal method would accurately classify targets that contain unknown variations with a minimal number of radar pulses.

A wideband, single pulse, manifold classifier is evaluated. The algorithm, deciBel Research’s Target Attribute Surface Manifold (dBTASM™), is tasked with correctly classifying the pieces of a ballistic missile complex. For this experiment, the algorithm has a database of only three objects, each representing a different piece of the complex. Against this database, missile pieces of different sizes and configurations were classified.

An effort to improve classification results through the use of different distance metrics was made. These metrics characterize the fit of the return pulse to the database, and thus they affect the robustness of the algorithm to object variations. Results were mixed; no distance metric proved clearly superior. Recommendations for future work are presented.
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Thanks both to my husband and my parents for ensuring that our Charlotte Jubilee was always surrounded by love, whether I was available or not.

Rejoice always, pray without ceasing, give thanks in all circumstances; for this is the will of God in Christ Jesus for you. Thessalonians 5:16-18
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<td>Attitude Control Motor: The part of a missile complex that provides slight adjustments to trajectory. It is attached behind the RV.</td>
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<td>deciBel Research Target Attribute Surface Manifold: A manifold matching classification algorithm.</td>
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<td>EMD</td>
<td>Earth Mover’s Distance: A cross-bin distance metric.</td>
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<td>I &amp; Q</td>
<td>In-phase and Quadrature Data: The real and imaginary components of a complex radar return.</td>
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<td>LFM</td>
<td>Linear Frequency Modulation: A chirp pulse is one with linear frequency modulation.</td>
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<td>NURBS</td>
<td>Non-uniform Rational B-Spline.</td>
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<td>RAI</td>
<td>Range Aspect Intensity: A plot of relative range and intensity versus aspect angle.</td>
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<td>RCS</td>
<td>Radar Cross Section: A $m^2$ unit that indicates how the target appears to the radar.</td>
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<tr>
<td>RTI</td>
<td>Range Time Intensity: A plot of relative range and intensity versus time.</td>
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<td>RV</td>
<td>Re-entry Vehicle: The part of a missile complex that re-enters the atmosphere and carries the warhead.</td>
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<td>Tank</td>
<td>Tank: The fuel tank of the missile complex that is attached behind the ACM.</td>
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CHAPTER 1

INTRODUCTION

One Pulse!

— Myles Harthun

1.1 Motivation

1.1.1 Importance of Classification

Efficient, accurate target classification is a challenging, critical problem in Missile Defense. The crucial question of classification is whether an object is lethal or non-lethal. If it is lethal, an interception must be attempted as soon as possible. If it is not lethal, the limited quantity of expensive interceptors must be conserved.

Several factors complicate this urgent classification decision of lethal versus non-lethal; these factors are described below.

Limited Radar Resources

Every radar’s timeline is fundamentally constrained by both duty factor and occupancy. Duty factor is the fraction of time that a radar can spend transmitting. This in turn can limit both the radar’s maximum pulse repetition frequency (PRF) and its maximum pulse width. Intuitively, typical duty cycle maximums are less than 50% as radars must have time to receive pulses return-
ing from (often) unknown ranges. Occupancy is the amount of time the radar is occupied with any activity, such as transmitting, receiving, or calibrating. Occupancy limits on a radar are near 100%, but can also limit the number of pulses processed in scenarios where duty cycle is not the restraining factor. That is, either of these restraints can cap radar operation and limit the number of pulses per target available to the mission planner for search, detection, track, and classification [7].

**Unlimited Potential Targets**

Within its restricted timeline a radar must process all available targets; only once they are classified as lethal or non-lethal is it safe to ignore non-lethal objects. Granted, certain limited techniques for mitigating this target processing requirement exist: they include the use of intelligence data (Is it coming from a hostile environment? Does its trajectory resemble a threat’s?), Identify Friend or Foe (IFF) (Is it squawking the friendly codes?), Cued radars (Is this target of interest to the mission planner?), Debris Mitigation Schemes (Without classification, are there trajectory, phase, or amplitude characteristics that are indicative of debris?). Unfortunately, large numbers of “targets” can be expected. Potential objects are listed below.

- Missile Raids: A large number of multiple-piece missiles launched at the same time.
• Solid Rocket Fuel: Motors powered by solid rocket fuel slough a large number of Aluminum Oxide debris pieces that have high Radar Cross Section (RCS) returns.

• Chaff: Light (inexpensive), numerous, high RCS pieces deployed to obscure the radar’s vision.

• Balloons: Light (inexpensive) objects to add targets that must be classified.

• Debris: Naturally occurring fragments, often with high RCS, that are sloughed off during missile separation.

From this list, it can be seen that hundreds of “targets” might appear in a scene, and that the traditional paradigm of detect, track, and classify can present a challenge to the radar’s constrained timeline.

**Imperfect Military Intelligence**

In order to decide what is lethal or not, lethality has to be defined. In ballistic missile defense, the warhead is contained on the re-entry vehicle (RV) which re-enters the atmosphere. To survive re-entry, these RVs are cone shaped; however, beyond that much variation can exist. For instance:

• Does the cone flare out at different angles, or is it streamlined (biconic/triconic or monoconic)?

• How long is it?

• What are its radii?
• Is it smooth or does it have rivets and brackets modeled?

For proper classification, an algorithm must either be robust to these variations or it must be used in conjunction with extensive scenario dependent databases that include all known target configurations. If military intelligence lags foreign technology, non-robust algorithms are subject to failure when an object is flown that is not contained in the database.

1.1.2 Current Classification Technique

Because of historical limitations on computer resources and processing power, traditional classification techniques were forced to reduce the huge amount of incoming pulse-return data to a few key values called features. These features strive to maintain the most important data in the pulse (typically the attributes of the pulse peaks), and discard the rest of the data for computational efficiency. Then with this reduced set of feature data, returning pulses are classified based on their statistical adherence to the features. That is, are the features of the returning pulse within a certain sigma of a target’s features in the database?

Regardless of the recent increases in computer processing power, these traditional feature extraction techniques are commonly in use today. Despite their common use, these features have serious shortcomings. First, these metrics are scenario dependent measurements of the target. As an explanation of the scenario dependence of features, consider the six blind men and the elephant (more realistic examples contain classified data).
Depending on where the radar is located and the environment in which it is propagating, a target’s features may resemble a wall, a rope, a tree, a fan, a snake, or a spear.

In addition, features discard valuable data which often leads to target classes overlapping. For instance, if you disregarded both temperature and texture in an effort to save space and processing time, a rope may resemble the lethal snake. Moreover, if this data-reduction induced similarity causes classification ambiguity more pulses are often scheduled to form a numerically stable guess at the target type. Thus, this method provides a classification guess with questionable accuracy at great additional cost to the radar’s constrained timeline [7].

1.1.3 Other Classification Approaches

Due to the shortcomings of features, other classification approaches are actively being researched both in the open literature and in classified circles. In the open literature two main approaches have emerged.
Transmit Pulse Optimization

Optimized transmit pulses can realize an increase in separation between target classes over the separation provided by the standard Linear Frequency Modulated (LFM) chirp pulse. However, this separation improvement depends on a database of impulse responses for every aspect angle of every potential target. Approaches for mitigating this a priori knowledge requirement are considered [8, 9].

Extinction Pulse Processing

Extinction Pulse (E-Pulse) post-processing uses a standard excitation transmit pulse and then processes the return with aspect independent E-Pulses that are designed to mitigate the late return of particular target types. Because the transmitted pulse can be generic across targets and the post processing pulses are generic across aspect, this technique alleviates some of the a priori knowledge requirements that plague both the feature and transmit pulse optimization approaches [2, 10–13].

An overview of these techniques will be given in the Background chapter.

1.1.4 TASM Classification Approach

deciBel Research’s Target Attribute Surface Manifold Classifier (dBTASM) capitalizes on both hardware and algorithmic improvements in computer processing to classify targets without discarding any data. Instead of relying on the data-reduction of features, dBTASM preserves all of the target’s complex return data in a mani-
fold representing scenario-independent attributes (typically either radar In-phase & Quadrature (I & Q) data or amplitudes ($\sqrt{I^2 + Q^2}$)). Then, with the data contained in this manifold, dBTASM applies an efficient, spline-based pattern matching technology to classify targets using a single pulse [3].

By classifying targets before track using a single pulse, the radar resource timeline is significantly aided by the dBTASM approach. However, the accuracy of one-pulse classifications needs to be quantified in both situations where the target is contained within a known database and (the more challenging case) when the target only resembles the generic objects in the database.

1.2 Problem Definition

This thesis will evaluate the abilities of dBTASM to correctly classify specific objects to generic classes using only one radar pulse. For instance, given a database with only three pieces of a generic missile complex, a re-entry vehicle (RV), attitude control motor (ACM), and fuel tank can dBTASM match a reference bi-conic RV to a longer monoconic RV using only one pulse?

1.2.1 Specific Goals:

1.2.1.1 Robustness Study

The first goal is to establish a baseline of performance for dBTASM. Specifically, how well can dBTASM match objects with size transformations and scatterer additions to a generic database containing only a RV, ACM, and fuel tank? To estab-
lish this baseline, a large variety of simulated objects are classified over all possible ‘look-angles’ using only one pulse. Objects are classified both at X-band with 1 GHz of bandwidth and at S-band with 300MHz of bandwidth.

1.2.1.2 Distance Comparison Alternatives

The second goal is to investigate improvements to dBTASM’s class ‘distance metric’. For each pulse, dBTASM evaluates the difference between the database models and the target return. The baseline dBTASM code uses the normalized sum of the squared range-bin differences to classify an object. After reviewing the literature, the performance of a variety of other comparison metrics was evaluated; these metrics include different bin-to-bin and cross-bin distances that might improve class separation and the robustness of classification results.

1.3 Summary

The robustness of dBTASM was evaluated by comparing varying RVs, ACMs, and fuel tank to a constant database containing a notional RV, ACM and fuel tank. These comparisons were made over all possible target look angles. Results were tabulated for three bin-to-bin distance metrics and one cross-bin technique with several configurations. Results were mixed, thus trends and indications for future work are presented.
CHAPTER 2

BACKGROUND

2.1 Literature Review of Other Classification Approaches

As mentioned in the introduction, target classification is a topic of active research. Several unclassified approaches, which do not rely on features, are reviewed below.

2.1.1 Extinction Pulse Processing

2.1.1.1 E-Pulse Paradigm

Regardless of the incident aspect and polarity of the transmitted waveform, data about the size, shape, and composition of a target reside in the Rayleigh and low resonance ranges of the radar return data. In fact, targets can be characterized by their complex, natural resonant frequency response within these regions. The characterizing complex, conjugate resonant frequency pairs are determined numerically or empirically for targets, and can be used to describe the late-time transient response of a target [12]. This late-time response reflects the transient, free-oscillation period of the target and is the sum of the target’s natural modes [10]
It is on this basis that Extinction Pulses (E-Pulses) are developed. E-pulses are aspect independent waveforms that are designed to eliminate (i.e. cause the extinction) of the inherent modal content of the radar return for a “matched” target in the late-time response. These E-Pulses are not transmitted to the target, indeed they are often too complex to synthesize for transmission. Instead an ultra-wide bandwidth, conventional waveform is transmitted, and the radar return is convolved with an E-Pulse matched to each target in the database. When the late-time results of this convolution are zero-modal (or in some designs single-modal), the target matches the database target [10].

Figures 2.1 and 2.2 show the late-time response of an object correctly matched to an E-Pulse and incorrectly matched to an E-Pulse. For these figures, the E-Pulse is generated for a dielectric sphere with a radius of 25mm. For the correct case with minimal late-time response, the E-Pulse was convolved with the matching dielectric sphere return. For the incorrect case, this E-Pulse was convolved with the target return of a brass cylinder with a radius of 22mm and a length of 100mm. The incorrect case demonstrates significant late-time response [2].
Figure 2.1: Correct E-Pulse Convolution [2]

Figure 2.2: Incorrect E-Pulse Convolution [2]
These two figures also show the complicated, noisy, early-time response. This early-time response is the forced response of the object and is ignored in this technique [13]. It is the late-time, transient response that visibly identifies the correct match.

To generate the E-Pulses, prior knowledge of every target’s natural frequencies is needed. For complex targets, this is achieved through building scaled models of each known target and measuring the late-time response. Thus, this technique relies heavily on a priori information. Researcher Kun-mu Chen (et. al) proposes a classification paradigm where every possible friendly target is built to scale so that the E-Pulses can be generated from the scale model’s measured data [11]. Each of these E-pulses would then be put in a database for comparison. If the convolution of the radar return with each pulse in the database yields significant late-time response the author recognizes this target simply as “unfriendly” [11]. This paradigm is not suitable for missile defense where unfriendly targets (and debris pieces) are likely to exceed the number of interceptors. Thus, further study on the robustness of E-Pulses to different object variations is needed.

2.1.1.2 Performance

Numerical simulations have verified the aspect independence of an object’s fundamental frequencies [2].

While there is some robustness to approximations of the modal content, inaccuracy of the synthesized E-pulse does lead to a degradation of performance in a way not yet quantified in the given papers. Numerical simulations have shown that the
E-Pulse technique is robust to random noise allowing for discrimination between the cylinder and sphere (described above) down to an SNR of approximately 5dB [2].

However, authors of several papers note that the majority of the signal strength is found in the early-time return, so 5dB SNR at the late-time return may require more radar resources than is intuitive [10, 11]. Finally, it is also noted that the target specific natural frequencies (represented by poles) influence the probability of discrimination. Targets which have higher frequency poles can be discriminated as low as 5dB SNR where as targets with lower frequency poles can need as much as 18dB SNR [10].

2.1.2 Optimizing Radar Transmission for Classification

When an object is illuminated by a wide-band pulse, the impulse response of the return will contain the electromagnetic scattering properties of the object. These properties are determined by the target’s unique geometry and material composition, so the returned scattering properties can be used as a fingerprint, or signature, for target classification [8]. In the following discussion of papers, the optimization of the radar transmit waveform is analyzed, such that the returning signature will have the maximum chance of correct classification.

This method, often referred to as matched illumination, optimizes the transmit pulse to maximize the Signal to Interference and Noise Ratio (SINR) of the return. The application for this method is two-fold. One, the increase in SINR can make targets easier to detect. Two, of interest here, matched illumination can maximize the square of Mahalanobis distance of separation between different target classes [8].
(The Mahalanobis distance is a measure of the distance between a point, \( P \), and a distribution, \( D \).

The optimized pulse concentrates energy into target and scenario specific frequency bands that help increase the similarity between the noise and clutter affected radar return and the true target. These bands correspond to the bands that have little clutter and large target responses. The resulting optimized pulse has a long duration and loses the range resolution provided by the standard linear-frequency modulation chirp [8].

The improvements in SINR for this method are benchmarked against the chirp pulse of the same total energy and duration, and have been tested in the literature at VHF and X-Band frequencies. Because performance improvement relies on a priori knowledge of the target’s frequency response, matched illumination is easier in the lower VHF frequency bands where the data is less sensitive to target geometry and aspect. At the higher frequencies of X-Band, the frequency return profiles are more complex and sensitive to target and target aspect changes [8].

Further studies have been done to analyze the robustness to aspect angle changes for this method. In these studies, it was found that at lower frequencies such as VHF, tolerable improvement over a chirp pulse was found as long as the aspect of the target was known to within 10°. At the higher frequencies of X-Band, the aspect of the target had to be known within one-half of a degree to maintain the improvement of matched illumination [9].

To mitigate this strict aspect requirement the interleaving of pulses matched to different targets and target aspects is proposed; this comes at the expense of the
radar’s timeline and a bank of parallel receive filters for each possibility. This approach is most tenable for the detection problem and not the classification problem under consideration [9]. Thus, this method does not eradicate the need of perfect military intelligence, and it does not mitigate the track before discriminate requirement that strains the radar’s timeline in dense environments and raid scenarios.

2.2 TASM Approach

In addition to feature based classification and the classification techniques surveyed above, manifold classification can be used, which is the TASM approach.

deciBel Research’s Target Attribute Surface Manifold (dBTASM) is a single pulse target classifier that capitalizes on the unique shape of target returns through the use of an efficient pattern matching technology based on Non-uniform Rational B-Spline (NURBS). Concisely, this algorithm compares every returned pulse to a pre-generated, scenario-independent database of target attribute surface manifolds (TASMs). These TASMs, which encapsulate all of the target’s physical properties, are compared to the radar return using the shape preserving NURBS. These NURBS allow the full data set to be efficiently shape matched to the pulse return [3].

The steps of the process are described in the following subsections.

2.2.1 TASM Database Generation

To generate the database, high fidelity target models are needed. Using an approach such as the Methods-of-Moments, the target’s I & Q data are modeled as a function of target aspect, roll, and polarization for all waveform frequencies to be
considered. Once modeled in the frequency domain, known sensor effects are added. For instance, if the radar beam is Taylor weighted the frequency model will be Taylor weighted at this point to make an equitable comparison. Known beam-forming biases are also taken into account at this time. Finally, this model is transferred to the time domain by using a Fourier Transform. To ensure a smooth surface in the time-domain, zero-padding may be used as necessary [3].

Once in the time domain, a uniform mesh of data points is extracted from this smooth surface. These data points define the NURBS representation of the surface. Specifically, they control the inflection of the surface at each point. These control points are the Node Base Formulation (NBF) of the surface and are each given an equal weighting [3].

Figures 2.3, 2.4, and 2.5 depict the generic RV, ACM, and Tank in the database.
Figures 2.6, 2.7, and 2.8 show the data stored in the amplitude TASM for the three generic database targets. For each TASM classification, every aspect angle slice of each plot will be compared to the return data.
Figure 2.6: Generic Database RV Time Domain TASM [3]

Figure 2.7: Generic Database ACM Time Domain TASM [3]
Figures 2.6, 2.7, and 2.8, which plot one roll cut of the principal polarization, demonstrate the amount of complex, distinguishing shape data preserved by the TASM method. In addition to saving the relative location of the peaks, the amplitude TASM database also preserves the lower amplitude data that still contains distinguishing structure. For instance, the RV and ACM aspect slices around 45° have no significant peaks; however, there are still distinguishing characteristics preserved. At this aspect, the RV has clear delineation between low level responses; the ACM does not have this clear delineation.
2.2.2 Radar Pulse Return Input Data

After the database has been generated radar returns can be classified. Each returning pulse contains an I & Q value for each range bin. This I & Q data inherently represents all of the sensor’s attributes including beam-forming effects and receiver noise as well as the target’s attributes [3].

2.2.3 NURBS Filtering of Radar Return

Before shape matching the returned pulse to the dBTASM database, a derivative based filter is applied to the return: the NURBS based Corner Cutting Algorithm (CCA). This derivative filter mitigates the effect of receiver noise (the white noise suppression is proportional to the number of nodes taken from the manifold and the number of derivatives applied with CCA) while preserving shape information. Contrast this to traditional matched filters that maximize signal to noise ratio at the expense of pulse shape [3].

2.2.4 AFFINE Scaling of the Return

Although the NURBS filtering effectively restores pulse shape, the added energy from receiver noise biases the power level of the pulse signal. To remove this added energy bias, the filtered return is scaled down according to the radar’s reported noise floor. Using the NURBS, this affine (shape-preserving) scaling can be done efficiently by only modifying the control points [3].
2.2.5 Find the smallest TASM Distance

The final step evaluates the distance between the scaled, filtered target return and the objects modeled in the database. For each target in the database, every aspect and roll angle is compared to the current radar return. Of all these object and angle comparisons, the best match is chosen. The current metric of comparison is the TASM distance. This normalized, bin-to-bin distance is calculated as the sum of the squared distances divided by the number of available points. This distance is calculated for all possible aspect angles of the database’s models and the scaled target return. Thus, the smallest TASM distance not only uniquely determines object classification, but it also inherently determines the viewing aspect angle. Because of this, one can classify an object and determine its body orientation relative to the radar in a single pulse [3].

The benefits of classification in one pulse, before target track, are obvious. This alleviates many constraints on the radar’s timeline; it allows more objects to be discriminated, the appropriate objects to be tracked, and more resources to be reserved to maintain target search. But how accurate are the one-pulse classifications for specific objects against a generic database? Moreover, is the TASM distance a robust metric for comparing targets with an inexact fit? Different distance metric possibilities are considered in the following section.
2.3 Literature Review of Distance Comparison Alternatives

For targets with imperfect matches in the database, the normalized sum of the square of the distance may not be indicative of the best target match. For instance, if an extra scatterer is added to a simple cone, the distance between amplitudes of the cone and the target in that particular bin may be significant enough to affect the entire TASM sum. Thus, techniques that minimize the effect of a few disparate bins are considered. In addition, techniques that can handle the shifting of peaks are investigated to bolster TASM’s robustness to objects with length variations [14].

With these criteria, both bin-to-bin and cross-bin comparisons were evaluated in the literature. Each of the techniques described below were evaluated with respect to processing speed, ease of implementation, and robustness for the expected data transformations.

When available, the processing speed is represented in Big O notation. This computer science notation describes how long an algorithm takes to complete with respect to the input size. In this case, the input, $N$, is the number of radar range bins to be compared. For example, the time an $O(N)$ algorithm requires increases linearly with the input size $N$. Whereas, the time an $O(N^2)$ algorithm requires rapidly increases with the square of the input size.
2.3.1 Bin-to-Bin

For bin-to-bin comparisons, each target bin is compared only to the corresponding database bin. These techniques typically process in $O(N)$ time and are easy to implement.

2.3.1.1 L1 (Manhattan)

The L1 distance is defined as

$$L1 = \sum_{i=1}^{N} |t_i - d_i|,$$  \hspace{1cm} (2.1)

where $N$ is the number of bins of the target, $t$, and the database, $d$.

This L1 distance is of interest in the ‘additional scatterer’ problem because by using an absolute value instead of a square, large differences between a single bin are dampened [15].

The L1 distance is often described as the Manhattan or City Block distance because it reflects the distance restrictions of walking down a city block. Instead of taking the shortest route between two points (Euclidean distance), the distance is measured as the distance in the x-dimension plus the distance in the y-dimension [15].

2.3.1.2 L2 (Euclidean)

The L2 distance is defined as
\[ L2 = \sqrt{\sum_{i=1}^{N} (t_i - d_i)^2}, \]  

where \( N \) is the number of bins of the target, \( t \), and the database, \( d \).

This L2 distance represents the intuitive definition of distance that is the shortest line between points, and is one of the most common measures of distance.

### 2.3.1.3 TASM Distance

The TASM distance is

\[ TASM = \sum_{i=1}^{N} \frac{(t_i - d_i)^2}{N}, \]  

where \( N \) is the number of bins of the target, \( t \), and the database, \( d \). This is the distance that dBTASM uses to measure target class separation [3].

### 2.3.2 Cross-Bin

For cross-bin comparisons, each target bin can be compared to a set of database bins; this 1 to \( N \) comparison allows flexibility to slight length changes and misalignments in the data. Typically cross-bin comparisons are more difficult to implement and slower to process.

#### 2.3.2.1 Earth Mover’s Distance

The Earth Mover’s Distance (EMD) is a flexible cross bin distance that provides an intuitive measure of the minimum amount of work needed to align binned
data. The metric accounts for how much data is shifted between bins and how far it is shifted [16]. Put another way, the Earth Mover’s Distance solves the problem of misaligned data as a transportation problem between bins; it is a measure of work [17]. When applied to the radar context, this equates to measuring both the shift and scale between the target return and the database.

Figure 2.9 illustrates the Earth Mover’s Distance. Three histograms are presented in the left column, \( h_1, h_2, \) and \( h_3 \). In this example, the EMD will be applied to compare \( h_1 \) to the latter two histograms. These results are shown in the right column. The EMD’s, Work = Force \( \times \) Distance, for both histogram comparisons is the same. That is, to match \( h_1 \) to \( h_2 \) two distance units of singular ‘force’ were applied (shifting both of \( h_2 \)’s peaks left). To match \( h_1 \) to \( h_3 \) two distance units of singular ‘force’ were applied (shifting one unit left and shifting one unit right). Thus, for these two very different histogram comparisons, the EMD is equivalent [4].

Although the EMD is equivalent for these comparisons, from a pulse matching perspective it is intuitive that \( h_1 \) matches \( h_2 \) better than it matches \( h_3 \). Indeed, \( h_2 \) is simply a time delayed replica of \( h_1 \). Thus, this simple example demonstrates that the EMD may not be an ideal cross-bin metric for a pulse matching application.
The original Earth Mover’s Distance algorithm is computationally expensive. Where most bin-to-bin metrics can be calculated in linear time with respect to the number of bins, $N$, the original implementation of the EMD was worse than $O(N^3 \log N)$ [16, 17]. Due to its usefulness, many attempts have been made to approximate it at a computationally feasible time.

An exact $O(N^2)$ solution was achieved by Haibin Ling and Kazunori Okada in situations restricting the shift distance penalty to an L1 metric. This algorithm uses a network flow optimization approach with spanning trees [17].

For low dimensional histograms and radar data, an approximate EMD solution has been developed to run in linear time, $O(N)$. This approximate approach relies
on using wavelets to subdivide the EMD problem to problems with specific scale and location [16].

2.3.2.2 Diffusion Distance

A novel $O(N)$ metric for the comparison of binned datasets is the diffusion distance [4]. In comparison to the EMD that finds the minimum work needed to shift and scale the data into sameness, this metric assumes a natural, diffusion process for scaling and shifting. Specifically, it defines the difference between data as a temperature field and, using the model of heat diffusion, measures how long it would take to equalize the data. In testing, it performs similarly to the Earth Mover’s Distance for data with large quantization errors (analogous to lower frequency data), but for data with fewer quantization errors, it did not perform as well as the EMD [4].

2.3.2.3 Quadratic Chi

Ofir Pele and Michael Werman developed the Quadratic-Chi Distance family. This distance family uses cross-bin normalization to suppress the influence of large bins such that small bins are still considered in a heuristic, intuitive way [5, 18]. In addition, a configurable, cross-bin similarity matrix provides robustness to shifted data [5].

This algorithm runs in $O(N)$ time and code is supplied in C and MATLAB at Ofir Pele’s website, which is given in the references [19]. As the quality of distance metrics depends on the nature of the data set, the algorithm comes with several key configurable parameters [5, 14]. The cross-bin similarity matrix allows users to
configure both the number of bins shifting that is allowed as well as the penalty for each bin shifted. In addition, the algorithm can be configured to use an L1 type metric (Eq. 2.1), L2 (Eq. 2.2) or to simulate the effect of any LP metric in between 1 and 2 according to equation 2.4.

\[
LP = \left( \sum_{i=1}^{N} |t_i - d_i|^p \right)^{\frac{1}{p}},
\]  

(2.4)

On the datasets presented in the paper, both tested configurations of this algorithm were shown to outperform the cross-bin EMD and the bin-to-bin L1 comparison for pulse shape matching applications [5]. An example is shown in Figure 2.10 and Table 2.1. For this example, the query is being compared to histograms a, b, and c. From an intuitive, pulse-shape matching perspective, the two-consecutive peak query most closely matches the two-consecutive peak histogram a; the match worsens for the three-consecutive peak b, and worsens still for the non-consecutive three peak case in c. This example compares the Quadratic Chi technique with a \( \chi^2 \) like normalization and a configuration that maximizes the normalization. For this example, only the Quadratic Chi techniques correctly matched the query to a. The Quadratic Chi techniques correctly sort the three histograms a, b, and c. Both the bin-to-bin L1 metric and the EMD incorrectly match the query to c.
Table 2.1: Comparison of Different Distance Metrics [5]
3.1 Robustness Study

To quantify the robustness of dBTASM to objects that are not included in the database, a variety of targets needed to be classified to the same generic database. Moreover, since this shape matching technique is aspect and roll dependent, every possible ‘look’ angle needed to be evaluated for each target. These basic requirements necessitate many runs; therefore, other parameters were fixed wherever possible.

Four principles guided the choice of remaining parameters. The other parameters must be unclassified, relevant, achievable, and elucidating.

3.1.1 Radar Setup

Most high resolution, target classification radars are at X-band. Thus, to be relevant to real world problems, the majority of the robustness study was performed at X-band. In addition, a cursory investigation into the use of older, lower band tracking radars was conducted. These radars are not typically relied on for classification because of the low resolution data returned. However, a brief robustness study was
conducted at S-band to determine if TASM can add classification ability to lower-band systems.

For both the X-band and S-band scenarios, bandwidth was evaluated at about 10% of the operating frequency [20]. For both scenarios linear frequency-modulated chirp waveforms were used. These waveforms were stretch processed [21].

All the scenarios were designed with a common noise floor. Using the noise floor approach allows TASM to be tested with realistic aspect and roll dependent Signal to Noise Ratio (SNR) fluctuations [22]. As robustness to noise was not the purpose of this study, a low noise floor of -40dB was chosen. This level provided SNRs of over 18dB for certain look angles, which is sufficient for classification with most approaches [10]. However, because the study uses one-pulse classifications at every look angle, much lower SNRs are also used to classify targets. As discussed in the background, the shape-preserving NURBs provide some noise suppression in these cases [3].

3.1.2 TASM Setup

In addition to radar scenario setup, a variety of TASM parameters had to be determined. For instance, how finely should the aspect and roll space be sampled? As the majority of the object variation was in aspect and not roll, the aspect resolution was set to 1°. The roll resolution was set to 30°; thus for every aspect angle, classification was performed at 0° roll, 30° roll, 60° roll, and 90° roll. Therefore, for each object tested, 180 Aspect Angles * 4 Rolls = 720 TASM Runs were performed. An experiment on a subset of data showed that finer aspect and roll sampling improves
the orientation estimates TASM provides, and slightly improves the classification results; however, the experiment used too much memory to apply to the full data set. (The TASM algorithm itself can run in real time on a modest machine; however writing out all the manifold data for post-processing in MATLAB was RAM and memory intensive.) Thus, rather than being optimal, these sampling choices were governed by limitations on RAM and memory.

Likewise, the TASM resolution option was configured based on computational necessity versus optimal performance. Using the shape preserving and enhancing properties of NURBs, the developer, Myles Harthun, has had success “increasing” resolution an order of magnitude over the theoretical bound,

\[
\text{Theoretical Range Resolution} = \frac{c}{2B},
\]

where the speed of light, \( c = 299792458 \text{m/s} \). The bandwidth, \( B \), is in Hertz and is 1GHz for the X-Band study.

Despite the developer’s success running cases with super-sampled resolution, physical resolution limits were used for the robustness study due to computing restrictions of the extensive test and post-processing matrix.

Results for both principle and orthogonal circular polarizations are presented.
3.1.3 Data Generation

3.1.3.1 Object Models

Both database objects and target returns begin with high-fidelity models of an object. These objects are drawn with a Computer Aided Design program (CAD). The surface material properties are assigned (i.e. is the material conducting?) and then the far-field electromagnetic scattering properties are determined. The object models for this study were generated by lucernhammer MT [23].

lucernhammer MT is a high frequency Radar Cross Section (RCS) calculation tool that relies on a variety of methods to predict the far-field signature return of an object. These methods include physical optics, physical theory of diffraction and shooting and bouncing ray methods [24]. The resulting signature is stored as a “data cube”. This cube of data contains the target response as a function of aspect, roll, polarization, and frequency [23].

Due to licensing issues, the objects used for this study were garnered from other unclassified projects performed at deciBel Research Inc.

3.1.3.2 Radar Returns

The radar returns are generated for every “look” angle using the deciBel Research tool TOAST. TOAST represents the radar return of a Target On A STick. Using this tool, the object, represented by the lucernhammer MT generated signature file, can be oriented at any desired aspect angle and roll by simply rotating the “stick”. Once the orientation is specified in TOAST, the target response for every
pulse is accessed from the underlying signature file and interpolated when necessary. Finally, the data are sent through the internal signal processor to generate the final target return’s I & Q data [23].

3.1.4 Example Input Data

Both the database and target input data are described in this subsection. First, basic object types are defined and described; next, target variations are described, and finally, example Range Aspect Intensity plots (RAI) are given to demonstrate the effect of object variations on radar returns.

3.1.4.1 Basic Object Types

The ballistic missiles considered by this thesis have three basic components. The reentry vehicle (RV), attitude control motor (ACM), and fuel tank. When launched, these objects are connected; the reentry vehicle is in the front, the attitude control motor is attached behind it, and the fuel tank is at the back of the object. As time progresses in the mission, this missile complex will break into the three separate components. These three components are described below.

RVs

Reentry vehicles (RVs) are smooth, cone shape objects that have rounded noses. They are designed to withstand reentry into the earth’s atmosphere, and carry the missile to its destination. Of the missile complex, identification of the RV is critical because it is the lethal object. Figures 3.1, 3.2, and 3.3 show an example RV shape.
Figure 3.1: Nose of RV [6]

Figure 3.2: Profile of RV [6]

Figure 3.3: Base of RV [6]
The RV in Figures 3.1-3.3 does not increase its radius linearly. Instead, there are very subtle angle changes; the most dramatic angle change can be seen in Figure 3.2 two horizontal lines from the bottom. Angle changes define the conicity of the RV. Monoconic RVs have no angle change (i.e. they have one conic angle), biconic RVs have one angle change (i.e. they have two conic angles), and triconic RVs have two angle changes (i.e. they have three conic angles).

The back of the RV is shown in Figure 3.3. In this example there is a cavity modeled, but the brackets that attach the RV to the ACM are not modeled.

ACMs

Attitude Control Motors (ACMs) attach behind the associated RV and can provide slight adjustments to the objects trajectory. These simple objects are typically shorter than the associated RV. The objects resemble a conic section without a nose. Figures 3.4-3.6 show an example ACM shape.

![Figure 3.4: Front of ACM](6)
The ACM in Figures 3.4-3.6 increases its radius linearly, thus it is monoconic.

The back of the ACM is shown in Figure 3.6. In this example a cavity is modeled, but the brackets that attach the ACM to the fuel tank are not modeled.
Tanks

Fuel tanks resemble cylinders with nozzles on the end. These objects attach behind the RV, ACM combination. Tanks are typically the longest object of the complex. Figures 3.7-3.9 show an example Tank shape.

Figure 3.7: Front of Tank [6]

Figure 3.8: Profile of Tank [6]
In addition to a cylindrical portion with a nozzle, Figure 3.8 illustrates that part of the tank has a conic section. From the view in Figure 3.7, it is clear that this example tank does not model the brackets that attach the ACM.

3.1.4.2 Object Variations

The objects variations described in this section were used to determine the robustness of TASM to object changes. These objects were compared to the reference objects of the database described in Figures 2.3, 2.4 & 2.5.

It is important to note that the reference objects do not represent the median of the variations. Instead, the reference objects typically are outliers from the target groups; this reference selection represents the most difficult classification problem for dBtASM. This approach was taken for two reasons. One, this selection of reference objects ensures that a priori test knowledge does not improve the results by designing a best case match in the database. Two, the reference objects were designed by the
developer of lucernhammer MT as generic, reference types; the targets flown were all designed for specific projects.

The reference RV was biconic and complex attachment mechanisms are modeled at the back end. It was approximately 1.8 meters long. This RV was compared against seven other RVs; none of the comparison RVs had attachment mechanisms modeled. Moreover, the comparison RVs were either monoconic or triconic; none of the comparison RVs were biconic like the database. All of the comparison RVs were significantly longer than the database RV (between 11% -39%). Most of the comparison RVs were significantly wider. Specifications are given in Table 3.1; in this table radii are given for the nose and tail of the RV and every additional conic section if applicable.
<table>
<thead>
<tr>
<th>RV</th>
<th>Conic</th>
<th>Length (m)</th>
<th>Radii (m)</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Database</td>
<td>Biconic</td>
<td>1.80</td>
<td>0.05</td>
<td>0.22</td>
<td>0.30</td>
<td></td>
</tr>
<tr>
<td>Triconic</td>
<td>Triconic</td>
<td>2.50</td>
<td>0.12</td>
<td>0.34</td>
<td>0.50</td>
<td>0.60</td>
</tr>
<tr>
<td>Beast 2</td>
<td>Triconic</td>
<td>2.00</td>
<td>0.26</td>
<td>0.33</td>
<td>0.40</td>
<td>0.60</td>
</tr>
<tr>
<td>Nodong</td>
<td>Monoconic</td>
<td>2.44</td>
<td>0.10</td>
<td></td>
<td>0.60</td>
<td></td>
</tr>
<tr>
<td>Unitary</td>
<td>Monoconic</td>
<td>2.15</td>
<td>0.10</td>
<td></td>
<td>0.60</td>
<td></td>
</tr>
<tr>
<td>RV B</td>
<td>Monoconic</td>
<td>2.05</td>
<td>0.07</td>
<td></td>
<td>0.40</td>
<td></td>
</tr>
<tr>
<td>Cone 7</td>
<td>Monoconic</td>
<td>2.01</td>
<td>0.08</td>
<td></td>
<td>0.33</td>
<td></td>
</tr>
<tr>
<td>Cone 8</td>
<td>Monoconic</td>
<td>2.00</td>
<td>0.10</td>
<td></td>
<td>0.35</td>
<td></td>
</tr>
</tbody>
</table>

Table 3.1: RV Objects Compared
The reference ACM was small and had complex attachment mechanisms to the RV modeled. It was compared to three other ACMs, two of similar size and one over 300% larger. All were missing the detailed attachment mechanisms. Specifications are given in Table 3.2; in this table the radii for both the front and back of the ACM are given.

<table>
<thead>
<tr>
<th>ACM</th>
<th>Cavity</th>
<th>Brackets</th>
<th>Length (m)</th>
<th>Radii (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Front</td>
</tr>
<tr>
<td>Database</td>
<td>Yes</td>
<td>Yes</td>
<td>0.61</td>
<td>0.32</td>
</tr>
<tr>
<td>Full Target</td>
<td>Yes</td>
<td>No</td>
<td>2</td>
<td>0.57</td>
</tr>
<tr>
<td>Beast 3</td>
<td>Yes</td>
<td>No</td>
<td>0.50</td>
<td>0.60</td>
</tr>
<tr>
<td>Simple</td>
<td>No</td>
<td>No</td>
<td>0.61</td>
<td>0.32</td>
</tr>
</tbody>
</table>

*Table 3.2: ACM Objects Compared*

The reference tank was small and had complex attachment mechanisms to the ACM modeled. It was compared to the only other available tank, which was
40% longer and 82% wider. The target tank did not have the same level of detailed attachment mechanisms modeled. Specifications are given in Table 3.3.

<table>
<thead>
<tr>
<th>Tank</th>
<th>Brackets</th>
<th>Length (m)</th>
<th>Radius (m)</th>
<th>Nozzle Radius Max (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Database</td>
<td>Yes</td>
<td>3.04</td>
<td>0.45</td>
<td>0.19</td>
</tr>
<tr>
<td>Full Target</td>
<td>No</td>
<td>4.26</td>
<td>0.82</td>
<td>0.5</td>
</tr>
</tbody>
</table>

Table 3.3: Tank Objects Compared

3.1.4.3 Effect of Object Variations

The object variations described in the previous section are significant and challenging. The changes in length, conic configuration, and complexity detailed affect the radar results in three distinct ways. These three effects are highlighted in the two Range Aspect Intensity (RAI) plot examples in Figure 3.10 and 3.11.

RAI plots are similar to the more familiar Range Time Intensity (RTI) plots, but are adapted to TOAST data, which varies with respect to aspect angle instead of time. These RAIs show the response of the database RV, which is biconic, 1.8
meters long, and has complex attachments modeled versus the unitary RV which is monoconic, and 2.15 meters long without attachments modeled on the back end.

Figure 3.10: X-Band Database RV RAI

Figure 3.11: X-Band Unitary RV RAI
The length of the target can be determined by examining the RAIs at 0° aspect. The relative range between peaks is slightly less than two meters for the 1.8 meter database RV of Figure 3.10 and slightly over 2 meters for the 2.15 meter RV of Figure 3.11. Changes of length are most evident at this point of the RAI, but also affect the RAI at other portions. These changes in length affect TASM classifications because they represent a ‘misalignment’ in data for bin-to-bin comparisons. Cross-bin techniques that allow some shifting of the data are expected to be more robust to length changes.

The conic configuration of the target can be determined from the number of bright flashes. The biconic RV in Figure 3.10 has two bright flashes at about 77° and 83°. The monoconic RV of Figure 3.11 has only one bright flash at about 79°. Mismatches in the conic configuration of objects will cause classification issues at the narrow band of aspect angles that are affected by the discrepancy. Since the affected regions are narrow in aspect angle, it is possible that TASM would be able to correctly classify the object at a slightly higher or lower aspect where the regions remain similar.

The difference in complexity detailed in the attachments at the backend of the target affects relative range measurements, amplitudes, and overall pattern of the radar return. This can be seen from about 100° to 180° in Figure 3.10 and 3.11. Cross-bin data shifting is anticipated to mitigate the effects of length distortions caused by this modeling difference. Techniques that dampen the effect of disparate bin amplitudes may minimize the effects of the amplitude changes occurring.
3.2 Metric Improvement Selection

Several techniques were chosen from the literature for post-processing the distance data. These techniques were evaluated with respect to processing speed, ease of implementation, and robustness for the expected data transformations. Using these criteria, all bin-to-bin techniques were selected due to their $O(N)$ processing time and ease of implementation. These bin-to-bin techniques include the L1, L2, and TASM distances.

Three cross-bin techniques were discussed in Section 2.3.2, the Earth Mover’s Distance (EMD), the Diffusion Distance, and the Quadratic Chi Distance Family. The Earth Mover’s Distance work-based model fails to capture the pulse shape of the radar return [16,17]. This shortcoming is specific to this study’s pulse matching goals and is demonstrated in Figure 2.9 [4,14]. Due to the suspected poor performance, long processing time, and complex implementation of efficient versions this technique was not tested [16,17].

Instead of the Earth Mover’s Distance work based model, the Diffusion Distance used an inherently different temperature flow model as a cross-bin distance metric between datasets. Despite the different models, the Diffusion Distance performed similarly to the Earth Mover’s Distance in tests by its developer on datasets resembling low frequency radar returns. On data resembling high frequency radar returns, the diffusion distance was not a reliable metric [4]. Thus, it was not tested.

The Quadratic Chi Algorithm was developed to adjust to the specific needs of the data application. The algorithm has two key configuration options, a cross-bin
penalty matrix that controls the availability of data to be shifted and an adjustable normalization factor that controls how much weight disparate peaks are given \[5, 14\]. The algorithm can run in \(O(N)\) time and came with a code library providing the basic functionality \[5\]. This technique was tested in addition to the bin-to-bin techniques.
CHAPTER 4

RESULTS

4.1 Bin-to-Bin X-Band Robustness Study

4.1.1 RV

The RV objects described in Table 3.1 were each compared to a database containing the database RV in Table 3.1, the database ACM in Table 3.2 and the database Tank in Table 3.3. Table 4.1 shows, for all possible look angles, the percentages of correct, one-pulse classifications.

<table>
<thead>
<tr>
<th></th>
<th>TASM</th>
<th>L1 Manhattan</th>
<th>L2 Euclidean</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Triconic RV</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Principal Polarization</td>
<td>68%</td>
<td>62%</td>
<td>68%</td>
</tr>
<tr>
<td>Orthogonal Polarization</td>
<td>30%</td>
<td>30%</td>
<td>30%</td>
</tr>
<tr>
<td><strong>Beast 2</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Principal Polarization</td>
<td>69%</td>
<td>68%</td>
<td>69%</td>
</tr>
<tr>
<td>Orthogonal Polarization</td>
<td>15%</td>
<td>15%</td>
<td>15%</td>
</tr>
<tr>
<td></td>
<td>TASM</td>
<td>L1 Manhattan</td>
<td>L2 Euclidean</td>
</tr>
<tr>
<td>----------------</td>
<td>------</td>
<td>--------------</td>
<td>--------------</td>
</tr>
<tr>
<td><strong>Nodong</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Principal Polarization</td>
<td>68%</td>
<td>65%</td>
<td>68%</td>
</tr>
<tr>
<td>Orthogonal Polarization</td>
<td>12%</td>
<td>12%</td>
<td>12%</td>
</tr>
<tr>
<td><strong>Unitary</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Principal Polarization</td>
<td>64%</td>
<td>59%</td>
<td>64%</td>
</tr>
<tr>
<td>Orthogonal Polarization</td>
<td>12%</td>
<td>12%</td>
<td>12%</td>
</tr>
<tr>
<td><strong>RV B</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Principal Polarization</td>
<td>66%</td>
<td>64%</td>
<td>66%</td>
</tr>
<tr>
<td>Orthogonal Polarization</td>
<td>10%</td>
<td>9%</td>
<td>10%</td>
</tr>
<tr>
<td><strong>Cone 7</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Principal Polarization</td>
<td>65%</td>
<td>63%</td>
<td>65%</td>
</tr>
<tr>
<td>Orthogonal Polarization</td>
<td>10%</td>
<td>9%</td>
<td>10%</td>
</tr>
<tr>
<td><strong>Cone 8</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Principal Polarization</td>
<td>64%</td>
<td>63%</td>
<td>64%</td>
</tr>
<tr>
<td>Orthogonal Polarization</td>
<td>9%</td>
<td>9%</td>
<td>9%</td>
</tr>
</tbody>
</table>

**Table 4.1**: Bin-to-Bin RV Results
The one pulse classification results were similar across all bin-to-bin comparisons. No consistent benefit was shown for any technique. The similarity in results for the TASM and Euclidean metrics was expected because the TASM metric is simply the squared Euclidean distance normalized by the number of bins. dBtASM can adjust this normalization factor through interpolation in certain situations; however, when this factor is constant across the database runs, no difference will be seen in the TASM and Euclidean correctness ratios.

The Orthogonal Polarization (OP) results were extremely poor for all objects. As the OP return is determined by non-smooth surfaces of an object, poor results for the smooth RVs were expected.

The database RV had the most predominant OP return because it had the most flat, intricate, connection detail modeled. Examples of the OP returns for the database RV versus a typical RV are shown in Figures 4.1 and 4.2.
From the plots above, it can be seen that the OP data is grossly dissimilar and not suitable for pulse-shape matching. This is particularly true for the higher aspect angles (the tail end of the objects) where the different level of modeling detail
becomes apparent. Because the performance of the OP results were so poor, no further analysis was done on characteristic failures.

The failures in the Principal Polarization (PP) single-pulse classifications were clustered into distinct bands by object. That is, swaths of look angles produced perfect classifications and other swaths of look angles produced nearly 100% misclassification. A typical example of this behavior is shown in Figure 4.3.

Figure 4.3 shows the PP, L1 classifications for RV B versus the database tank. Every possible aspect angle is shown along the X axis (roll angles have been decimated for simplicity). The Y axis simply indicates if RV B was correctly classified as an RV, 0, or incorrectly leaked to the tank class, 1. The narrow aspect regions of error shown are typical for the PP results.

Figure 4.3: RV B Classifications as the Tank
Although the ratio of correct classifications was similar across all of the objects, the trends in misclassification differed slightly by object. These trends are discussed below.

**Back End**

All but the Triconic RV and Unitary RV had a substantial number of misclassifications at the back end of the object—roughly from 165° to 180°. In these instances, the tank was typically the false-target classification. Two explanations are apparent for misclassification at the back end. One, the amount of detail modeled on the back end of database RV was higher than that modeled on the targets. This would cause some discrepancy between the expected pulse shapes. Two, all of the target RVs were significantly larger than the database RV. For this reason, the larger tank may produce a better fit at these late aspect angles. It is unclear why the Triconic and Unitary RV did not suffer from tail misclassification.

**Nose**

All but Cone 7 and Cone 8 suffered from a few misclassifications at the nose. Cone 7 and Cone 8 flare to a radius most similar to the database RV; thus, it is easier to classify these as the RV. The remaining objects all flare to a larger dimension, which more closely resembles the tank that they are classified as.

**Conical Configuration**

Remaining failures tended to be more dispersed from broadside to tail of the
RV. These failures often occurred in bands, which appear to be related to the different conical orientations of the RVs.

4.1.2 ACM

The ACM objects described in Table 3.2 were each compared to a database containing the database RV in Table 3.1, the database ACM in Table 3.2 and the database Tank in Table 3.3. Table 4.2 shows, for all possible look angles, the percentages of correct, one-pulse classifications.

<table>
<thead>
<tr>
<th>Full Target ACM</th>
<th>TASM</th>
<th>L1 Manhattan</th>
<th>L2 Euclidean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Principal Polarization</td>
<td>64%</td>
<td>76%</td>
<td>64%</td>
</tr>
<tr>
<td>Orthogonal Polarization</td>
<td>31%</td>
<td>31%</td>
<td>31%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Beast 3 ACM</th>
<th>TASM</th>
<th>L1 Manhattan</th>
<th>L2 Euclidean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Principal Polarization</td>
<td>45%</td>
<td>87%</td>
<td>45%</td>
</tr>
<tr>
<td>Orthogonal Polarization</td>
<td>18%</td>
<td>18%</td>
<td>18%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>ACM Simple</th>
<th>TASM</th>
<th>L1 Manhattan</th>
<th>L2 Euclidean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Principal Polarization</td>
<td>47%</td>
<td>91%</td>
<td>47%</td>
</tr>
<tr>
<td>Orthogonal Polarization</td>
<td>15%</td>
<td>9%</td>
<td>15%</td>
</tr>
</tbody>
</table>

Table 4.2: Bin-to-Bin ACM Results
The OP results were quite poor for all objects; this was to be expected, and is (analogously) explained in the previous RV section. However, it is significant to note that the OP returns were not causing false alarms as the non-lethal ACM was overwhelmingly misclassified as the non-lethal tank. In a database including only the RV and the ACM, results were better than 90%. However, due to the poor results using the full database, no further analysis was done on OP returns.

Unlike the RV case, the ACM results differed significantly by bin-to-bin comparison technique. The PP classifications are strikingly better for the L1 bin-to-bin comparison than the L2 and L2-based TASM results. It was theorized in Chapter 2, that the L1 metric would be better for dampening the results from largely disparate bins because the differences were not squared. The data show that L1 metric was successful in borderline areas where the L2 based metrics made the wrong call. However, both metrics consistently misclassified on the broadside of the target from approximately 90° to 120°. In this challenging region there are minimal effects from the distinguishable nose and tail of the object. This region constitutes the brightest, lengthless returns of the target so any slight mismatch of peak location is significant even without the squaring effect of the L2 metric.

Note, that unlike with the benign ACM and Tank swap seen with the OP returns, these PP classifications constitute expensive false alarms where non-lethal ACMs are called to be lethal RVs.

The Full Target ACM was classified as the RV more often than the other two ACMs. This is expected because the Full Target ACM has a length more closely resembling the database RV than the database ACM.
4.1.3 Tank

The Tank object described in Table 3.3 was compared to a database containing the database RV in Table 3.1, the database ACM in Table 3.2 and the database Tank in Table 3.3. Table 4.3 shows, for all possible look angles, the percentages of correct, one-pulse classifications.

<table>
<thead>
<tr>
<th>Tank</th>
<th>TASM</th>
<th>L1</th>
<th>L2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Principal Polarization</td>
<td>9%</td>
<td>5%</td>
<td>9%</td>
</tr>
<tr>
<td>Orthogonal Polarization</td>
<td>91%</td>
<td>91%</td>
<td>91%</td>
</tr>
</tbody>
</table>

Table 4.3: Bin-to-Bin Tank Results

The tank is unique in that the OP results were excellent and the PP results were poor. The poor PP results were unexpected, but they may have been affected by the asymmetric intensity of the tank. As shown in Figure 4.4, the strong intensity difference between the lead and tail scatterer may have contributed to the tank appearing to be shorter, resembling one of the smaller objects.
Figure 4.4: PP: Full Target Tank RAI

The OP results were expected to be better for the tank because the tank’s unique back end with a nozzle provide significant, identifying OP returns. The target tank’s OP RAI is shown in Figure 4.5. In addition the OP responses for all of the database targets are shown (Figures 4.6-4.8). From these it is clear that the OP tank has enough structure to easily be matched.
Figure 4.5: OP: Full Target Tank RAI
Figure 4.6: OP: Database RV RAI

Figure 4.7: OP: Database ACM RAI

Figure 4.8: OP: Database Tank RAI
4.2 Cross-Bin X-Band Robustness Study

The Quadratic-Chi Distance Family was evaluated to determine if cross-bin metrics could improve the robustness of dBTASM classifications. This cross-bin algorithm constitutes a family of metrics that vary by the normalization used and by the tolerance for shifting bins.

4.2.1 Algorithm Configurations

4.2.1.1 Normalization Factor

This algorithm allows the normalization factor to be easily changed. This normalization is intended to variably suppress the effect of a few bins with large discrepancies from disguising the rest of the matching characteristics. All TASM distances were tested with two normalization factors. The first, the $\chi^2$-Like-Normalization, is intended by the authors to have the same dampening effect as the bin-to-bin $\chi^2$ metric. The second normalization metric was chosen to have the maximum dampening ability on the effect of grossly disparate bins. This dampening ability is limited in the algorithm by restrictions on continuity and stability to about 80% more normalization than the $\chi^2$-Like normalization \[5\]. This second test will be referred to as the Practical-Maximum-Normalization.

4.2.1.2 Shifting Matrix

The robustness and sensitivity of bin-to-bin metrics is inherently constrained by the number of bins used. For instance, if a signal is finely sampled with bins very
subtle differences in the signal can be distinguished. However, this finely sampled case is less robust when matching signals with slight shifting of the peaks. It is here that cross-bin algorithms have an advantage. [5]

When testing the Quadratic Chi Distance Family, two cross-bin shifting matrices were used. One was designed to allow the data to be shifted with approximately a 30% penalty for each bin shifted. This case was run on all of the data. A second case was designed for the tank, which had large discrepancies in length between the database and the target flown.

For the tank tests, the length of the flown target was approximately 1.25 meters longer than the database target. To allow each peak to shift $\frac{1.25}{2} = 0.625$ meters the shifting matrix needed to allow a shift of at least 8 bins. (Range windows were approximately 20 meters with 256 bins.) Thus, the shifting matrix was designed to add a 12.5% penalty for each shifted bin.

Even with this significant shifting allowance, the majority of the peak contribution will be diminished by the shifting matrix for this case where the object length is 40% greater than the model.

Such omniscient matrix design would be inappropriate in a tactical system. Two mitigations are suggested, which might be used either in conjunction or independently.

**Increased Database to Limit Transformations**

An array of database objects could be modeled at even intervals of length. This
array would thus limit the shifting that would be needed to match important pulse peaks.

**Adaptive Database Analysis**

The shifting matrix could be designed through an automated analysis of all of the objects in the database. That is, a pre-processing algorithm could look at the minimum peak shift delta between the objects. The matrix would then be designed to limit the shifting to an amount less than this delta, which would allow misclassification.

**4.2.2 RV**

The results for the RV runs are given in Table 4.4 for both normalizations and the standard shift penalty.

<table>
<thead>
<tr>
<th>Triconic RV</th>
<th>(\chi^2)-Like-Normalization</th>
<th>Practical-Max-Normalization</th>
</tr>
</thead>
<tbody>
<tr>
<td>Principal Polarization</td>
<td>44%</td>
<td>6%</td>
</tr>
<tr>
<td>Orthogonal Polarization</td>
<td>4%</td>
<td>39%</td>
</tr>
<tr>
<td><strong>Beast 2</strong></td>
<td>(\chi^2)-Like-Normalization</td>
<td>Practical-Max-Normalization</td>
</tr>
<tr>
<td>Principal Polarization</td>
<td>56%</td>
<td>0%</td>
</tr>
<tr>
<td>Orthogonal Polarization</td>
<td>1%</td>
<td>67%</td>
</tr>
<tr>
<td></td>
<td>$\chi^2$-Like-Normalization</td>
<td>Practical-Max-Normalization</td>
</tr>
<tr>
<td>----------------</td>
<td>----------------------------</td>
<td>-----------------------------</td>
</tr>
<tr>
<td><strong>Nodong</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Principal Polarization</td>
<td>37%</td>
<td>0%</td>
</tr>
<tr>
<td>Orthogonal Polarization</td>
<td>5%</td>
<td>60%</td>
</tr>
<tr>
<td><strong>Unitary</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Principal Polarization</td>
<td>34%</td>
<td>2%</td>
</tr>
<tr>
<td>Orthogonal Polarization</td>
<td>11%</td>
<td>39%</td>
</tr>
<tr>
<td><strong>RV B</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Principal Polarization</td>
<td>57%</td>
<td>0%</td>
</tr>
<tr>
<td>Orthogonal Polarization</td>
<td>2%</td>
<td>57%</td>
</tr>
<tr>
<td><strong>Cone 7</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Principal Polarization</td>
<td>37%</td>
<td>0%</td>
</tr>
<tr>
<td>Orthogonal Polarization</td>
<td>7%</td>
<td>44%</td>
</tr>
<tr>
<td><strong>Cone 8</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Principal Polarization</td>
<td>44%</td>
<td>0%</td>
</tr>
<tr>
<td>Orthogonal Polarization</td>
<td>8%</td>
<td>57%</td>
</tr>
</tbody>
</table>

**Table 4.4**: Cross-Bin RV Results
The OP results for the $\chi^2$-Like-Normalization were consistently misclassified as the tank. It should be noted that these are misclassifications of the worst kind; leakage, where a lethal object is declared non-lethal and ignored. When the normalization factor was increased to the Practical-Maximum-Normalization, the OP results improved significantly, but still allowed an unacceptable amount of leakage in three swaths at the nose, broadside, and tail.

The PP results suffered when the normalization factor was increased to the 'Practical-Maximum'. In this case, the RVs were typically leaked into the ACM class.

Overall, the performance of the bin-to-bin metrics was superior to the results of this cross-bin metric where the chosen normalization factor always affects one polarization poorly.

### 4.2.3 ACM

The results for the ACM runs are given in Table 4.5 for both normalizations and the standard shift penalty.
<table>
<thead>
<tr>
<th></th>
<th>$\chi^2$-Like-Normalization</th>
<th>Practical-Max-Normalization</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Full Target ACM</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Principal Polarization</td>
<td>72%</td>
<td>78%</td>
</tr>
<tr>
<td>Orthogonal Polarization</td>
<td>5%</td>
<td>9%</td>
</tr>
<tr>
<td><strong>Beast 3 ACM</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Principal Polarization</td>
<td>95%</td>
<td>100%</td>
</tr>
<tr>
<td>Orthogonal Polarization</td>
<td>7%</td>
<td>8%</td>
</tr>
<tr>
<td><strong>ACM Simple</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Principal Polarization</td>
<td>85%</td>
<td>100%</td>
</tr>
<tr>
<td>Orthogonal Polarization</td>
<td>16%</td>
<td>45%</td>
</tr>
</tbody>
</table>

**Table 4.5**: Cross-Bin ACM Results

The OP results were like the bin-to-bin metrics. The results were poor, with most ACM look angles being misclassified due to the lack of definitive OP returns. That said, because the non-lethal ACM was misclassified as the the non-lethal tank, expensive false alarms and dangerous leakage did not occur.

The PP cross-bin results were exceptional. For the two ACM targets that closely resembled the database in length, perfect performance was achieved for the Practical-Maximum Normalization, and very good performance was achieved for the $\chi^2$-Like-Normalization. The Full Target ACM realized only slight improvement over
the bin-to-bin metrics. As discussed with the tank case, this is due to the shifting penalty being too severe for the length discrepancy. The misclassifications for the Full Target ACM were false alarms that were primarily from 90° aspect to 130° aspect.

4.2.4 Tank

The results for the tank runs are given below for both normalizations factors, the standard shift penalty, and a reduced shift penalty designed to accommodate the large discrepancy in tank length between the database and flown target.

<table>
<thead>
<tr>
<th>Full Target Tank</th>
<th>$\chi^2$-Like-Normalization</th>
<th>Practical-Max-Normalization</th>
</tr>
</thead>
<tbody>
<tr>
<td>Principal Polarization</td>
<td>6%</td>
<td>7%</td>
</tr>
<tr>
<td>Orthogonal Polarization</td>
<td>90%</td>
<td>70%</td>
</tr>
</tbody>
</table>

**Table 4.6:** Cross Bin Tank Results: Regular Shifting Penalty

<table>
<thead>
<tr>
<th>Full Target Tank</th>
<th>$\chi^2$-Like-Normalization</th>
<th>Practical-Max-Normalization</th>
</tr>
</thead>
<tbody>
<tr>
<td>Principal Polarization</td>
<td>39%</td>
<td>32%</td>
</tr>
<tr>
<td>Orthogonal Polarization</td>
<td>91%</td>
<td>73%</td>
</tr>
</tbody>
</table>

**Table 4.7:** Cross Bin Tank Results: Reduced Shifting Penalty

The $\chi^2$-Like-Normalization, Regular Shift Tank results closely mimic the bin-to-bin results. Like for the bin-to-bin case, the failures are distributed over look...
angle and object. As with previous results, a slight improvement was seen in the OP case for Maximum-Practical-Normalization, and a significant degradation in the PP results was seen using the Maximum-Practical-Normalization. Despite the decrease in performance for the PP Maximum-Practical-Normalization, it is interesting to note that the failure distribution was markedly different from earlier tank cases. Instead of the failures being dispersed over look angles, the failures are narrowly focused around 55°, 90°, and 170°.

The tank runs that were designed to improve the PP classifications by reducing the shifting penalty were successful. Even with the still significant shifting attenuation, these runs realized approximately a 30% increase in correct classifications. OP results were essentially unaffected.

4.3 S Band

At S Band, the following objects were compared.

<table>
<thead>
<tr>
<th>Object</th>
<th>Length (m)</th>
<th>Radius (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Database RV</td>
<td>1.8</td>
<td>0.05 0.30</td>
</tr>
<tr>
<td>Beast 3 ACM</td>
<td>0.5</td>
<td>0.6 0.75</td>
</tr>
<tr>
<td>Database Tank</td>
<td>3.0</td>
<td>0.45 0.45</td>
</tr>
<tr>
<td>Beast 2 RV</td>
<td>2.0</td>
<td>0.12 0.60</td>
</tr>
</tbody>
</table>

Table 4.8: S Band: Database and Target
4.3.1 Bin-to-Bin Results

The bin-to-bin results for these objects are shown in Table 4.9.

<table>
<thead>
<tr>
<th>S Band Beast 2 RV</th>
<th>TASM</th>
<th>L1 Manhattan</th>
<th>L2 Euclidean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Principal Polarization</td>
<td>2%</td>
<td>2%</td>
<td>2%</td>
</tr>
<tr>
<td>Orthogonal Polarization</td>
<td>2%</td>
<td>2%</td>
<td>2%</td>
</tr>
</tbody>
</table>

Table 4.9: S Band: Bin-to-Bin Results

The results were uniformly bad; after several correct classifications at the nose, the remaining classifications were either the ACM or Tank. Both misclassifications represent the worst case scenario of lethal to non-lethal leakage.

4.3.2 Cross-Bin Results

The cross-bin results for these objects are shown in Table 4.10.

<table>
<thead>
<tr>
<th>S Band Beast 2 RV</th>
<th>$\chi^2$-Like-Normalization</th>
<th>Practical-Max-Normalization</th>
</tr>
</thead>
<tbody>
<tr>
<td>Principal Polarization</td>
<td>3%</td>
<td>3%</td>
</tr>
<tr>
<td>Orthogonal Polarization</td>
<td>2%</td>
<td>1%</td>
</tr>
</tbody>
</table>

Table 4.10: S Band: Cross-Bin Results

As with the bin-to-bin metrics, the results were uniformly bad. After several correct classifications at the nose, the remaining classifications were either the ACM
or Tank. Both misclassifications represent the worst scenario of lethal to non-lethal leakage.

### 4.3.3 Comparison to X-Band Results

With less than one third of the bandwidth of the previous study, the 300MHZ bandwidth S-Band case presents a more challenging classification problem for most techniques. The initial results indicate that dBTASM is not robust at S-Band. The developer has had success running more heavily noised S-Band targets with noiseless matches in the database by using NURB Splines to super-sample and interpolate the resolution. This technique should be evaluated for robustness at S-Band.
5.1 Summary

5.1.1 Accomplishments

Twelve different objects were compared to a generic database at a uniform sampling of all possible look angles. 8688 dBTASM distance sets were evaluated using three different bin-to-bin metrics, and a cross-bin metric with two normalizations and two different shifting penalties. Results for 1GHz X-Band data and 300MHz S-Band data were considered.

This type of robustness analysis had never before been performed by deci-Bel Research or the algorithm’s developer. The results were mixed. The one-pulse classifications were strongly affected by polarization changes and metric changes. Unfortunately, the effects varied by object making it difficult to recommend a static, universal approach.

The L1 Manhattan bin-to-bin metric showed some promise for borderline PP calls on ACMs, and in other cases was competitive to the L2 Euclidean and L2-based
TASM metric. The cross-bin metrics performed poorly on the RV class, but showed potential for the ACM and the tanks.

The configurations for the cross-bin metric algorithm are powerful and might be adaptively configured to great advantage. This topic is discussed in Section 4.2.1, but more work is needed.

Direct comparison to the reviewed classification techniques in the literature is not applicable. The robustness of the Extinction Pulse Processing is not quantified. The Transmit Pulse Optimization papers did not claim robustness.

5.1.2 Challenges

A number of challenges were encountered along the way. These included hardware issues, dB TASM issues, and verification issues.

Hardware Issues

Initially, the processing was to take place at work on an unused server with extensive RAM and a 64 bit MATLAB license. However, a contract issue regarding the use of the server arose and it was taken down without warning. All data and scripts that were not remotely backed up were lost.

Next, the processing continued on a desktop computer with storage on a shared network device. The shared network device became infected and the IT department was forced to roll it back to a previous week. Again recent data and scripting were lost.
Processing continued on that computer with a 64 bit professional MATLAB license. However, runs exhausted the limited RAM and were too lengthy using swap space.

Finally, the runs were moved to a personal computer with much more RAM. However, the student MATLAB license was restricted to 32 bits and the processing failed because it could not map enough memory space. At this point, extensive optimization was done in order to proceed.

**dBTASM Issues**

The robustness testing was performed while dBTASM was undergoing rapid development and maturation. During the course of this research, over four versions of the algorithm were used as bug fixes and improvements were implemented. Each new version invalidated old results, and required patience, additional C coding, and script adjustment.

**Verification Issues**

This robustness study was designed and performed independently, although it was at the request of deciBel Research’s management. This independence allowed work to be done on a flexible timeline and reduced the chances of scrutiny when grossly different objects were tested with sometimes poor results. However, this independence also blocked access to the wisdom of the developer and engineers with more experience analyzing radar returns.

As such, much effort went into vetting results without the benefit of experience to say what “looked right”. For instance, initial results showed consistent, con-
siderable improvement of the L1 Manhattan distance over the other methods. However, when analyzing the scripts, it became clear that a manifold parsing error had occurred. When this error was corrected, the amazing L1 Manhattan results disappeared. This mistake demonstrated the data-driven variability of the metric results and the difficulty of verifying processes when the answer is unknown.

5.1.3 Future Work

A variety of limitations were placed on this robustness study to establish a baseline. In the future, these limitations should be removed so that the full potential of dBTASM can be quantified.

Investigations should include the following:

- Quantify the effects of using the shape of the I & Q data instead of just the amplitude data.
- Quantify improvements from super-sampling in range space using NURBs.
- Quantify improvements from modeling the database file’s frequency data at a higher fidelity.
- Quantify effects of bin-to-bin metrics with bin specific normalizations (for instance the $\chi^2$ distance).
- Quantify degradations from noise.
In addition, other techniques could be considered for improving the results. If more than one pulse is available TASM’s ‘best-of’ option evaluates the object’s classification history and attempts to correct spurious results. Given the nature of the failures seen in the robustness study (large bands of error free calls with localized patches of complete error), this ‘best-of’ technique could be very effective for tumbling targets or any targets that are viewed at a variety of look angles during the track.

In conjunction with the ‘best-of’ feature, TASM also inherently provides a ‘confidence-in-classification-score’. Since each pulse is compared to every target in the database, the known separation between class results provides an indication of confidence.

TASM currently has the option of classifying based on one polarization or a uniform combination of the available polarizations. A uniform OP and PP weighting adds stability since the tank classified best with OP returns and the other objects performed best with PP returns. Still, a more idealized weighting might be developed that increases separation between the target classes in the database.

Database design is another area of study. The addition of a few more parameterized database objects could limit the amount of misclassification without significantly increasing runtime or modeling expense. For instance, simply including two versions of each object that bounded the size variations of the class may significantly improve results.

Finally, an effort to configure a robust cross-bin metric in conjunction with a priori knowledge of the database is recommended.
REFERENCES


