Passive Radar Imaging and Target Recognition using Illuminators of Opportunity

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SUMMARY

Passive radar systems that exploit illuminators of opportunity, such as FM radio and television broadcasts, to detect and track airborne targets have been under development for over a decade. This paper reviews efforts to add radar imaging and target recognition capabilities to such systems. We discuss recent developments along two parallel threads:

1) Target recognition via radar cross section (RCS) profiles: In this approach, databases of the RCS of targets at different incident and observed angles are created using method-of-moments computational electromagnetics codes. The extracted RCS profiles for different targets, scaled to account for antenna patterns and atmospheric propagation, are compared to the collected data. A coordinated flight model is used to estimate the aircraft's orientation along its flight path. The low frequencies used in passive radar naturally give stable features well suited for automatic target recognition.

2) Radar imaging: A traditional inverse synthetic aperture approach to forming images with passive radar data results in severe artefacts due to the sparse and irregular Fourier sampling patterns resulting from realistic data collection scenarios. We review the application of a recent optimization-based, region-enhancing imaging algorithm to passive radar imaging that effectively suppresses these artefacts, and illustrate the difficulties posed by the underlying multidimensional autofocus problem.

1.0 INTRODUCTION

Traditional active radar systems transmit waveforms and deduce information about targets by measuring and analyzing the reflected signals. A radically different approach to radar arises when we consider that modern civilization is already drenched in transmissions such as FM radio, television, and cell phone signals. Passive radar systems that "hitchhike" off of such existing "illuminators of opportunity" remain covert compared to their active brethren. Other covert sensors, like as ESM sensors employing multilateration,[1] are available, but *they rely on the assumption that the objects of interest are broadcasting and don't mind announcing their presence*. PCL sensors require no such assumption. We save on the cost of building a transmitter, since another party has already gone through the trouble. However, communication signals were not designed with radar applications in mind. The cost of the radar system then shifts from traditional radar hardware to the digital signal processing know-how and horsepower required to make sense of the received signals. The price of radar hardware remains relatively fixed, while the cost of computational power continues to plummet.

[1] For example, see http://www.roke.co.uk/download/datasheets/multilateration.pdf.

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Passive radar can thus boast something active radar cannot: its further development is primarily driven by Moore's law. The passive radar approach has often been referred to as PCL (Passive Coherent Location.) To our knowledge, the term PCL was first coined by Dick Lodwig and colleagues at what was then IBM, later Loral, and currently Lockheed Martin. The term PCL is closely tied with Lockheed Martin's Silent Sentry series, of which Silent Sentry 3 is the latest incarnation, although the acronym PCL has evolved to refer to passive radar systems in general. The term PCR (either "Passive Coherent Radar" or "Passive Covert Radar") has also become popular. Interest in PCR has skyrocketed in the past five years. International conferences on PCR were hosted by Roke Manor in the United Kingdom in June 2002, and by the University of Washington in Seattle in the United States in October 2003. At the time of writing, the IEE Proceedings Radar, Sonar, and Navigation is preparing a special issue devoted to PCR guest edited by Paul Howland (NATO C3 Agency) and Paul Gilgallon (U.S. Air Force Research Lab).

A three-year DARPA-sponsored program at the Univ. of Illinois at Urbana-Champaign on the "Design and Optimization of Passive and Active Imaging Radar" began in the Fall of 1998. A prime thrust of this effort was the development of ways to add automatic target recognition (ATR) and radar imaging components to passive radar systems. Follow-up efforts (some in collaboration with colleagues at MIT and Univ. of Michigan Ann Arbor) have continued at Georgia Tech, sponsored by NATO NC3A, AFOSR, startup funds from Georgia Tech's School of Electrical and Computer Engineering, and the Demetrius T. Paris Professorship. This paper briefly reviews some of this work, and points out some avenues for further research.

2.0 AUTOMATIC TARGET RECOGNITION

One approach to target identification compares the collected data to target libraries synthesized using electromagnetic codes. To ensure robust classification in the presence of noise and errors in estimates of position and orientation, it is helpful if the Radar Cross Section (RCS) of the targets vary "slowly" with small changes in these components of the state vector. The variation in RCS, as characterized by the number of nulls encountered as a target's aspect changes, is proportional to the electrical length of the target. At FM-band frequencies (100 MHz), a fighter-sized aircraft is approximately five wavelengths long. In contrast, at the X-band frequencies used by many active radars (10 GHz), the same aircraft would be 500 wavelengths long.

In the late 70's and early 80's, a series of papers [1-3] illustrated that low frequencies are quite natural for target classification. Those papers had active radars in mind, but low-frequency radar did not catch on in the West since most of the desired spectrum has been allocated to communications. PCR systems, on the other hand, which directly exploit existing long wavelength emissions that are convenient for target recognition, circumvent the frequency allocation problem faced by active radars.

2.1 Joint Tracking/Recognition with Particle Filters

Target tracking and target recognition are generally considered to be separate tasks. In particular, target tracking algorithms generally track two-dimensional or three-dimensional target positions in Cartesian coordinates via simple constant velocity or constant acceleration models; target orientation is generally not directly accounted for. The notion that tracking and recognition algorithms could help one another dates back to work by Sworder and colleagues [4-6]; in particular, the authors suggest using imaging information to detect manoeuvre changes. Sensors detailed enough to provide target recognition data generally can also provide orientation; in fact, orientation must often be estimated as a nuisance parameter. The orientation and position of aircraft paths are clearly coupled. Miller, Srivastava, and Grenander [7] suggest fusing the recognition and tracking tasks into a single joint estimation problem.

Picking up this thread, Herman [8-9] followed up on an earlier suggestion [10] to conduct joint recognition and tracking from passive radar data using particle filters. Instead of trying to form two-dimensional Inverse Synthetic Aperture Radar (ISAR) or one-dimensional range profiles to provide the "imaging data," Herman used the raw RCS. This avoided issues relating to calibrating phase information. Since high-frequency codes such as XPATCH are not accurate at the long wavelengths of interest in passive radar, the RCS of different targets was simulated from CAD models using the method-of-moments code FISC (Fast Illinois Solver Code) [11-12].

2.2 ATR with a Coordinated Flight Model

Herman's joint tracking/recognition approach described in the previous section is quite complicated to implement, and computationally intensive because of the particle filter. This prompted the search for a simpler method that could perhaps be implemented in real-time in the immediate future. Drawing from traditional aerodynamics texts, Ehrman created a simple algorithm for finding the likely orientation sequence of an aircraft given a flight path [13], and considered ATR from passive radar RCS data using the orientation sequence estimated by that algorithm [14-16], assuming the track estimated by the tracker to be correct. This is a simpler feed-forward strategy than Herman's approach, in that the results of the RCS data are not fed back into the tracker. Ehrman also considered atmospheric propagation and antenna pattern effects not considered by Herman (although they could easily be adapted and included in Herman's procedure).

Ehrman's initial studies considered vertically polarized data, and gave quite encouraging results on a four-class problem consisting of a Falcon-20, a Falcon-100, a T-38, and a VFY-218.[2] When horizontal polarization was considered [17-18], an interesting phenomenon was observed: for a complex path derived from an instrumented F-15 flight, the Falcon-20 was never correctly identified, even at low noise levels. This pointed out the limitation of the simple coordinated flight model. In essence, the Falcon-20 at the estimated orientation looked more like the Falcon-100 at the correct orientation than the Falcon-20 at the correct orientation! Thus, Ehrman's PhD work is currently moving in the direction of jointly estimating the orientations and target type from the data (although still not as complex as jointly estimating the orientations, target type, and positions from the data as in Herman's approach.) The coordinated flight model can provide a mean, and the algorithm can search in an "error ball" of orientations around that mean.

2.3 Performance Analysis

In some scenarios, we might expect aircraft to be flying around certain common flight paths (for instance, routes between airports). In these situations, it may be reasonable to ask: how long do we need to collect data for a particular aircraft before we can make a decision about its type with a certain degree of accuracy? Ehrman [19] has been considering information-theoretic measures [20], such as relative entropies (i.e. Kullback-Leibler distances [21]) and Chernoff distances, as means of approximating probabilities of error without having to conduct extensive Monte Carlo simulations. As part of her ongoing PhD work, Ehrman has computed approximations for these information-theoretic distances between Rician distributions, which are appropriate for slowly fluctuating targets.

[2] The VFY-218 is not a real aircraft; it is a CAD model commonly used by the computational electromagnetics community.

2.4 The Difficulty of Computing Scattering Databases

The scattering databases needed for ATR consist of complex reflectances sampled over the five-dimensional space of incident azimuth, incident elevation, observed azimuth, observed elevation, and frequency. A full viewing sphere of bistatic angles is needed to accommodate manoeuvring aircraft. To reduce the time complexity of creating such databases, especially using computationally intensive codes such as FISC, it is helpful to sample the space as sparsely as possible while maintaining accuracy. Sampling densely enough to satisfy the Nyquist criteria requires a tremendous amount of computing time.

There is a need for the development of informative scattering models that will permit sampling at a rate below the Nyquist limit. In the high-frequency regime, the electric current induced on a metallic scatter by an incident electromagnetic wave tends to clump at the corners of that object; hence, scattering center models are quite powerful [22-25]. At low frequencies, the current tends to spread out over the aircraft; radar images take on a distributed appearance, instead of the point-like appearance often seen at high frequencies. Thus, to make this approach to ATR practical for a large number of targets, novel techniques and models will need to be developed.

2.5 Helicopter Blade Modulation

For helicopters, the Doppler modulation lines arising from blade motion form a strong target type discriminant. The ability to identify different helicopter types using active low-frequency radar has been demonstrated by Kuschel (see Section 2 of [26]). We do not know of any PCR-specific studies along these lines, although it is clearly a ripe area for exploration.

3.0 IMAGING

In the previous section on ATR, most of the discussion focused on using raw RCS data. One could also conduct ATR using, for instance, ISAR images or range profiles. Considering the difficulty of forming ISAR and related images from passive radar data, we have found it easier to use raw RCS for ATR, since phase errors are not an issue in using RCS. However, radar images may be useful in their own right. There may always be targets present that are not in the ATR system's library, and in such cases it would be useful to have some sort of image to present to a human analyst.

3.1 Nonlinear vs. Linear Imaging Models

The "nonlinear vs. linear" question may have two different meanings in this context. In one meaning, it refers to the *underlying data model*, i.e. whether the quantities of interest map linearly to the data space. In the other meaning, it refers to the *processing of the algorithm*, i.e. whether the algorithm is a linear transformation of the received data.

At the beginning of the DARPA project mentioned in the introduction, much effort was focused on nonlinear data models, including forays into the distorted Born iterative method [27] and the so-called "linear sampling" methods [BLW] (which are not really linear) of Colton, Kirsch, and colleagues. While these efforts are interesting in their own right, they may be overkill for the passive radar problem, and nonlinear imaging models may be a red herring in this context. Indeed, if extensive data are available, simple inversion methods based on linear models produce surprisingly superb images, as discussed in the next section.

Ye, Bresler, and Moulin [29-31] developed several interesting two-dimensional contour estimation techniques, along with associated performance bounds, for both linear and nonlinear data models. To be practical, these should be extended to the three-dimensional case.

3.2 Nonlinear Algorithms for Linear Models

In traditional radar imaging using linear data models, the received complex radar data can be thought of as samples of the Fourier transform of the image of interest. If a sufficient amount of data is available in a sufficiently concentrated region, one can simply zero-pad the parts of Fourier space where data is unavailable and take a two-dimensional inverse Fourier transform. Using this technique on low-frequency data sets derived from FISC yields images that, remarkably, resemble optical images of the aircraft, far more than at microwave frequencies, where the images have a point-like appearance. The trouble is that to form such an image, unrealistically rich data sets are needed. In a realistic collection scenario, the available data is strongly limited by the collection geometry, and straightforward zero-padding usually leads to unrecognizable images [32-33].

The sampling patterns arising in passive radar bear a passing resemblance to those found in radio astronomy; hence, it became natural to try algorithms from radio astronomy such as CLEAN. Unfortunately, the complex-valued and distributed nature of passive radar images lead to disappointing results from CLEAN [34]. CLEAN works best on images that are point-like in nature, such as microwave radar images, whereas low-frequency radar images are more evenly distributed throughout regions. This led to a search for a more sophisticated technique, such as Çetin's [35-36] region-enhanced nonquadratic optimization techniques. In this approach, an objective function is formulated that combines a term indicating fidelity to the data with a term incorporating prior knowledge about likely images. The term chosen encourages smoothness within regions while allowing sharp edges between regions. When applied to the same passive radar examples used in [31], the region-enhanced technique was found to provide remarkable improvements [37]. Along another path, Ye, Bresler, and Moulin [38] developed a level-set based method for reconstruction from sparse Fourier samples, which should be revisited in this context.

Another issue that may arise is the angular dependence of radar reflection. At high frequencies, reasonable cross-range resolution may be obtained using data from a small angular extent. At low frequencies, data may need to be collected over a wide range of angles to obtain good cross-range resolution. Some wide-angle imaging algorithms, based on Wigner-Ville distributions, are proposed in [39].

3.3 The Autofocus Problem

In an ISAR imaging scenario, the distance from the radar platform to an airborne target must be known to demodulate the received radar signal and retrieve the imaging data. When this distance is not known exactly, a phase error term results that corrupts the imaging data. The effect is a phase error function, varying with each received echo, which acts as a blurring filter, defocusing the radar image. All of the studies described in the previous section assumed there was no such phase error. Autofocus algorithms create an estimate of this phase error function to correct the defocused image. Such a capability will be a vital component of any working imaging system.

Existing autofocus algorithms developed for ISAR imaging assume a monostatic scenario. This assumption implies a single transmitter is colocated with a single receiver, and large bandwidth pulses are available to illuminate targets. The sampled Fourier imaging data collected under these conditions form a two dimensional polar ribbon in frequency space. The angular extent of this ribbon corresponds to the received echos, and the radial extent to the samples from each echo. Here the phase error varies only with echo, or with the angular dimension.

In a passive radar-imaging scenario, multiple transmitters, such as different FM radio and/or television signals operating at different frequencies, are used to illuminate the airborne targets. The advantage of this scheme is stealthiness; targets are unaware that they are being watched. However, several drawbacks make forming images challenging. First, the tracking data produced by a passive system is not as accurate as that of a conventional active system. Secondly, unlike active systems, which employ specially crafted high bandwidth pulses, passive systems must rely upon narrowband FM or TV signals, which are essentially an impulse in the frequency domain when thought of from an imaging standpoint. Consequently, only a thin arc of Fourier data is collected from each station, in contrast to a two dimensional polar ribbon associated with a single active wideband transmitter. In the passive scenario, the range from transmitter to target to receiver must be known to demodulate the received radar signal. Inaccurate target position estimates result in inaccurate calculated two-way ranges, and thus phase errors appear. Because the transmitters are located at different positions, and operate at different frequencies, the phase error function corresponding to each station, or each arc in frequency space, will be different (though related by the geometry). Thus, we cannot think of the autofocus problem as compensating for a phase error function that varies in only one dimension. We effectively have a two-dimensional autofocus problem.

We might conjecture that a passive radar autofocus algorithm should be built around correcting the trajectory of the aircraft itself rather than directly estimating phase errors. Although the phase error functions corrupting multiple arcs of Fourier imaging data are different, they are related by the underlying geometry. We seek the trajectory that most closely resembles the actual trajectory, and consequently results in the best image. The autofocus perspective turns this on its head, and seeks the best image, which consequently may give a better track. A measure of image sharpness may be utilized as a cost function in determining the best trajectory. Several such measures, such as the entropy of the image, are available [40]. Morrison [41-42] has conducted further work in this direction.

4.0 CONCLUSIONS

This paper has reviewed recent efforts to develop ATR and radar imaging technologies appropriate for passive radar systems. Radar imaging is particularly difficult, as problems of sparse Fourier samples, angle-dependant scattering, and phase errors need to be overcome. The first two problems have been considered extensively, but they have been considered *separately*. Bringing solutions to all of these challenges together into a single algorithm will be extremely challenging.

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