Advanced Methods of Automatic Target Recognition Based on Spectral Sensing

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ABSTRACT

Many realistic detection problems cannot be solved with simple statistical tests for known alternative probability models. Uncontrollable environmental conditions, imperfect sensors, and other uncertainties transform simple detection problems with likelihood ratio solutions into composite hypothesis (CH) testing problems. Recently many multi- and hyperspectral sensing CH problems have been addressed with a new approach. Clairvoyant fusion (CF) integrates the optimal detectors ("clairvoyants") associated with every unspecified value of the parameters appearing in a detection model. For problems with discrete parameter values, logical rules emerge for combining the decisions of the associated clairvoyants. For many applications with continuous parameters, analytic methods of CF have been found that produce closed-form solutions–or close approximations for intractable problems. Here the principles of CF are described, and references are supplied for many solved problems. Although a host of spectral-specific algorithms have been developed, this new fusion methodology applies to any multivariate detection problem.

1.0 DREAMS OF ATR

For the past 30 years (or more), the dream of achieving automatic target recognition (ATR) using methods of spatial image analysis has struggled to achieve any operational successes. However, recent ATR approaches using nonliteral sensing modalities such as multispectral or hyperspectral imagers have not only shown greater promise. Some have been fielded and used extensively to find a variety of targets of military/intelligence value. The maturing of the newer sensing technologies also prompted advanced developments in classical statistical detection theory (SDT).

Under most operational conditions, although the mathematical form of optimal detectors might be known, they cannot be implemented, because they require knowledge of unmeasured physical parameters associated with the environment. Nevertheless, robust detection algorithms have been developed that leverage those detectors. Robustness is achieved by *fusing* the optimal detectors over all possible parameter values. And the fusion principles, although well defined, remain flexible enough to accommodate many practical problems, such as the presence of outliers, which lie outside the scope of probabilistic modeling.

The use of target detection principles based on recent SDT advances can be contrasted with a recent ATR pivot to the world of artificial intelligence in the form of deep learning artificial neural networks (ANNs). Such methods require extensive target training on large databases which, moreover, can prove difficult to populate, especially in intelligence applications. By contrast, effective spectral imaging methods have been developed that require ZERO training on the targets.

For example, "dark" (clandestine) sea-going vessels can be found [29] in satellite-based spectral imagery with a statistical method using no target information. The fusion idea in concert with a relatively simple stochastic mixing model of the background enable this method of anomaly detection. Because the target pixels occupy a small fraction of the total data, their slight corruption of estimated background statistics has a minimal effect on detection performance. By contrast, ANN training requires truth data, and (typically) tens of thousands of target exemplars. The utility of statistical methods becomes apparent in any detection problem for which extensive training data is unavailable.

Another spectral SDT application has appeared in the detection of explosive chemicals with algorithms [30] that can be enhanced as incremental knowledge of target and confuser signatures is collected on the battlefield. Such performance enhancement is not feasible for neural networks, which generally do not learn from single events without the risk of overtraining.

These applications exemplify the fundamental difference between SDT and ANN approaches. SDT methods rely on physical models of the relevant phenomenology and can leverage human knowledge accumulated over centuries of science. And as more prior information becomes available, models can be modified and incorporated into the detection methodology. By contrast, ATR methods based on ANNs attempt to mimic the human capacity to recognize shapes, a poorly understood mechanism that takes even a human brain many years to develop. The use of physics-based modeling along with mathematics to construct detection algorithms can be thought of as the use of deep *learned natural* neural networks–human brains–as contrasted with the data-driven methods of *deep learning* artificial neural networks.

2.0 TWO KINDS OF UNCERTAINTY

Most wide area surveillance problems assume no knowledge of the material present in any pixel. Construction of detection algorithms for such environments implies that sensed data at any pixel must be treated as a random variable. Here we discuss one of simpler detection models, in which background and target distributions in a feature vector **x** are known. In remote sensing with an imaging spectrometer, **x** is a list of a pixel's radiance intensities at discretized wavelengths that can number in the thousands or as few as three. However, the fusion principles described here are not limited to spectral applications. They apply to any multivariate detection problem, including other electro-optic modalities, such as polarization and image sequences.

2.1 The case of known parameter values

The simplest statistical model of the detection problem admits an optimal family of solutions. These detectors can be expressed with a *discriminant* function

$$d(\mathbf{x}:t,c,\lambda)=\frac{p_T(\mathbf{x}:t)}{p_C(\mathbf{x}:c)}-\lambda. \tag{1}$$

The probability density functions (pdfs) for the target (*T*) and clutter (*C*) appearing in the ratio depend not only on the feature vector **x**, but also on sets of parameters *t* and *c*, respectively. When these have known values, positive values of the discriminant function (1) define the "critical" region, which is the set of feature vectors $\{\mathbf{x}\}$, i.e. pixels, that are classified as targets by the algorithm.

The likelihood ratio (LR) test defined by (1) is characterized by two performance parameters, the probability of detection P_D and the probability of false alarm P_{FAR}. Both these can be increased (decreased) by decreasing (increasing) the value of the threshold λ, which can be adjusted by the user.

However, regardless of the choice of threshold, the detector in (1) is *indomitable.* Its two performance parameters cannot simultaneously be matched or beaten by any other detector, a consequence of the Neymann-Pearson lemma [1].

2.2 Realistic detection problems

Some of the target and background parameters in the sets t and c appearing in (1) can depend on unmeasured environmental conditions. For example, a prediction of a target's spectral signature in the field is often a physics-based extrapolation from a laboratory measurement. Thus, the mean target signature appearing in p_T in equation (1) depends on a host of atmospheric conditions: column densities of aerosols, water vapor, carbon dioxide, source and magnitude of illumination, etc.

These environmental parameters exemplify *epistemic* variables, which are fixed but have unknown values, as distinguished from random variables, such as the feature vector **x**, with which a probability distribution can be associated. This means that the ratio in (1) cannot be evaluated, because parameters that specify the form of the pdfs might have unknown values.

Nevertheless, even when some parameter values are unknown, the tests described by (1), called "clairvoyants," [1] can still be useful as performance metrics. For example, robustness of performance by a candidate detector can be gauged by computing how far its performance deviates, as a function of parameter values, from that of the (optimal) clairvoyant detectors of (1).

The fusion methodology, on the other hand, finds a new use for clairvoyants–in the creation of new classes of robust detectors.

3.0 CLAIRVOYANT FUSION

New families of detectors have been created by a process that fuses clairvoyant detectors over all values of t and c in (1). The specific rules differ [2], depending on which type of parameter, target or clutter, is being varied in the fusion process. For target parameters, the clairvoyants' decisions are logically ORed; for clutter parameters they are ANDed. This is equivalent to combining the clairvoyants' critical regions by the set-theoretic UNION or INTERSECTION operations, respectively.

The logic rules for fusing are of no practical use when the number of parameter values is infinite. For example, if a parameter is continuous. However, Ref. [3] derived an alternative algebraic method based on discriminant functions. The fused discriminant function is given generally by

$$d_F(\mathbf{x}) = \underset{c}{Min}\left(\underset{t}{Max}\left(d\left(\mathbf{x}:t,c,\lambda(t,c)\right)\right)\right) . \tag{2}$$

Notice that the threshold is allowed to vary with the distribution parameters. The functional form of λ, which defines the fusion *flavor*, usually contains at least one intrinsic degree of freedom, so that (2) defines a family of tests, just as an LR test does by virtue of its variable threshold value λ. Ref. [2] introduced two particularly useful flavors of fusion: CFAR and CPD. In the first, all fused clairvoyants are constrained to produce identical false alarm probabilities; in the second, identical detection probabilities.

Also, refs. [2] specifically and [3] generally showed that choosing the fusion flavor corresponding to a constant λ, independent of distribution parameters, produces the generalized likelihood ratio test (GLRT). This standard answer to the unknown parameter question dates to the early 20th century. Clairvoyant fusion therefore explains the GLRT in a new context, fixing it as the "classical limit" of the detection theory embodied in (2).

3.1 Solved detection problems

Statisticians call detection problems with unknown parameter values composite hypothesis (CH) testing problems. All the published solutions to CH spectral detection problems model both target and clutter classes with elliptically contoured distributions (ECDs). The general ECD form

$$p(\mathbf{x}) = f\left((\mathbf{x}-\mu)^t C^{-1}(\mathbf{x}-\mu)\right) \tag{3}$$

depends only on first- and second-order statistical quantities, the mean value μ and the covariance matrix C. These can in turn depend implicitly on environmental parameters with possibly unknown values, and they also differ according to which class the pdf describes, target or clutter.

For example, ref. [2] considered the problem of rejecting shadowed pixels in an anomaly detection algorithm. The clutter was modeled with a general unimodal ECD and a mean and covariance estimated from a set of (relatively) bright pixels. Then CFAR fusion over an unknown scale factor appearing in both μ and C produced a detector that allowed the proper classification of all pixels that are identical, except for a scale factor that models illumination level. The problem exemplified linear subspace models. That fused detector (CAD–"Conical Anomaly Detector") was studied subsequently in ref. [4].

Ref. [2] also compared CAD to the standard GLRT, but this required a more specific model. There and in several subsequent papers, the common multivariate normal (MVN) form was chosen:

$$p(\mathbf{x}) = \frac{\exp\left(-\frac{1}{2}(\mathbf{x}-\mu)^t C^{-1}(\mathbf{x}-\mu)\right)}{\left[(2\pi)^N \det(C)\right]^{\frac{1}{2}}} \ . \tag{4}$$

Of course, the values of μ and C depend on whether p describes the target or background distribution. The model in (4) also appeared in ref. [2] as part of a standard additive-target CH problem. It was shown that CFAR fusion trivially produces the uniformly most powerful solution for all false alarm rates, a quality lacking in the corresponding GLRT. This superiority to the ubiquitous classical method spurred many of the subsequent investigations of fusion-based solutions to a variety of problems.

Each of the fusion flavors in ref. [2] was derived both analytically, using (2), and geometrically, using the set-theoretic interpretation. When the parameters are continuous, the decision boundary around the fused critical region is the envelope of the clairvoyants' critical regions, and this can sometimes be discovered by inspection. When it cannot, the Max/Min formulation in (2) can be used to define an analytical approach. This formulation first appeared in limited form in ref. [2] (for at most one target and one clutter parameter) and was proven in general in [3]. The latter marked the end of the early purely theoretical work underpinning the fusion rules. Soon thereafter other interpretations appeared [5,6].

Ref. [3] also considered a nonlinear (affine) subspace model, as well as a Laplacian distribution model. The CFAR flavor for the MVN version was derived in [7], producing a family of Affine Matched filters.

In [8], the concept of folded subspaces was introduced. A generalization of an earlier technique [9], it has proven invaluable for interpreting high-dimensional data and in facilitating the design of effective fusion flavors. Ref. [8] also indicated how one flavor, which defines an intractable problem for the Laplacian affine subspace model, could be transformed into an approximate CPD problem that is solvable in closed-form. No iterative methods were needed.

Ref. [10] compared CFAR, CPD, and GLRT solutions to the MVN affine subspace problem. Ref. [11] derived the exact solutions for the affine Laplacian model and made quantitative comparisons using short-wave infrared hyper-spectral imaging data. It also demonstrated for the first time that the "one-sided" ACE detector, long a staple in the hyperspectral imaging community, could be derived as a fusion method, using a clutter model reasonable for remote sensing applications. The usual derivation of ACE relies on a model that is irrelevant [12] to spectral remote sensing. It also produces a double-cone symmetric decision boundary, one of which is unphysical for hyperspectral imaging applications and is usually excised in practice [13].

Ref. [14] exemplified a new use of fusion methods. A multi-modal fusion problem was considered, in which disparate sensors measure the values of two variates, whose correlation level is unknown. The GLRT has no simple closed-form solution. However, by interpreting it geometrically as a fusion method, an alternative detector ("fixed-intercept fusion") that approximates the GLRT was devised that does have a closed-form solution. The idea of solving for or approximating the conventional GLRT by using fusion methods was repeated in later work. The use of geometrical arguments to approximate new types of fused detectors had been introduced in the "approximate affine CPD" [8], applied to a Laplacian model.

Ref. [15] introduced "common-parameter" problems. These involve epistemic variables with values that are unknown, but are the same for target and background hypotheses, a subtlety not distinguished by the GLRT. For such models, the fusion interpretation of the GLRT is intuitively incorrect, in that it results from a fusion over parameters treated as independent, rather than constrained. This means that the fusion process includes extraneous combinations of target and background parameters. For this type of problem, properly constrained "constant likelihood ratio" (CLR) fusion produces detectors that differ from the GLRT and produce superior performance.

Ref. [15] also derived the CFAR-fused answer to the homoskedastic (equal covariance matrices for target and background distributions) gaussian affine 1-D subspace problem. That work was extended in [28] to include the CPD fusion flavor.

Ref. [16] applied fusion concepts to the multispectral detection of ships at sea, using 8-band commercial satellite data. It modeled clutter as a mixture of sea and clouds at unknown levels. This model treated a sub-class ("ampliskedastic") of MVN heteroskedastic models, using two new flavors of detection algorithm. The paper also demonstrated how the folded subspace concept could be applied with more than one "faithful" dimension, producing a 2½ -dimensional representation of 8-dimensional data. The fusion flavors were designed to allow discrimination (target-from-target) as well as detection. This was achieved by analytically sculpting the decision boundaries of independent detection algorithms so that their critical regions do not overlap. Fusion detectors thus began serving double duty, as detectors and discriminators.

Clairvoyant decision boundaries for the ampliskedastic MVN model are hyperspheres, and these happen to be the same as for the additive target model using a t-distribution model [17-19]. Therefore, a corollary benefit of fusion solutions for the ampliskedastic gaussian models is their applicability to t-distribution models, as well.

Ref. [20] treated two new common-parameter problems. The first corresponds to unknown sensor bias. The fusion solution was compared to the usual "invariance" approach to this type of problem. The second such problem solved by fusion methods was a generalized version of the one solved in ref. [15], but now allowing variances as well as mean values to be scaled with a common parameter.

Primarily a survey of prior results, [21] also quantified the improved performance of a fusion-based algorithm (called L^3R [11]) that addressed an affine subspace detection problem for a Laplacian distribution model. It was applied to short-wave infrared hyperspectral data. Ref. [22] also applied fusion methods to satellite-based data, to detect ships at sea in commercial multispectral visible/infrared imagery.

The performance of an indomitable decision rule [23] cannot be matched by any other rule uniformly (that is, for all realized parameter values). Ref. [24] extended the theory of "clairvoyant fusion" (this phrase first appeared in [25]), showing how a discrete fusion problem could be converted into a continuum fusion problem whose solution is indomitable. The result generalizes to all discrete fusion detection problems [26]. That is, fusion methods can produce every indomitable solution to any discrete fusion problem. It is likely that this principle holds for continuous fusion problems as well. In short, every theoretically optimal detector can be derived by fusing elementary likelihood ratio tests.

Physically consistent ("replacement") models for electro-optic spectral detection of opaque targets had not been solved with prior theoretical methods. In ref. [27] the general model was shown solvable with fusion techniques, and solutions were found for several particular variants of the model. Also, an invariance property of the general fusion methodology was used to simplify and find a GLRT solution for one variant of the problem.

Finally, ad hoc method called simplex-ACE [31] has been proposed, to supplement the ACE detector in situations where several spectral realizations of a single target signature are known. The new method is based on a geometric extrapolation of ACE, generalizing it as a projection onto a simplex instead of onto a linear subspace. Simplex ACE has also been derived from fusion principles, as a CFAR-flavor of ACE [32]. Furthermore, the more relevant application of simplex-ACE is to the detection of target mixtures, and for this CPD fusion is more appropriate. A closed-form expression for CPD-ACE has also been derived. It cannot be derived with the geometric method used for simplex-ACE in [31].

4.0 SUMMARY

This paper describes the current state of research in methods of clairvoyant fusion, which reformulates the usual approach to the composite hypothesis testing problem from "How to pick the optimal detector" to "How to use the collection of all optimal detectors." It also synopsizes a compendium of problems solved with fusion methods. A variety of CH models, each with its own special issues, have been addressed. These include: the problem of outliers, from either target or clutter sources; a constraint to accommodate a capability for discrimination (target from target); and the solution of some (joint) CH problems not addressed by the classical GLRT method.

Fusion methods have also been used to solve intractable GLRT problems, by replacing them with related fusion problems for which closed-form solutions can be derived. And at least one ad-hoc method has been re-interpreted as a fusion method, and this led to a more general class of fusion-based detectors.

The fusion methodology has been shown to have important theoretical properties. It appears that any indomitable solution to a detection problem can be produced by a fusion method. And every cost-minimizing solution to a detection problem is a member of the indomitable class. It is likely that this principle holds as well for problems with continuous parameter values. The varied practical utilities of the fusion methodology that have been demonstrated along with its foundational theoretical aspect justify the concept of a "fusion school" of detection theory.

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