AUTOMATED NODAL ANALYSIS FOR CRT DISCRJMINATION AND VA I. IDATION

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Abstract

In the ASAS Program Office TechBase thrust* on Automated Nodal Analysis, JPL has chosen to address a problem of major applicational significance to the US Army, i.e., Critical Relocatable Target (CRT) identification and geolocation. This data fusion problem coalesces two issues fundamental to the development of Reconnaissance, SillV['illillC(and Tactical Assessment (RSTA) technology: enabling real-time capability for in-situ processing of tactical intelligence data, and developing a paradigmatic framework amenable for implementation on computational platforms ranging from surveillance satellites to ruggedized workstations. Enabling conceptual and computational formalisms are developed, that synergistically exploit limited sensor sightings of enemy facilities / equipment and associated logistics supply train, terrain features, Order of the Battle (OB) knowledge, and weather impact on *a priori* known mobility characteristics of a force entity, to predict presence envelopes for CRTs

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I. INTRODUCTION

The primary objective of this data fusion task is to develop an Automated Nodal Analysis (ANA) system, enabling conceptual and computational analyses in the area of Intelligence Preparation of the Battlefield (11)11), The main focus is the investigation of several analytical problems related to (i) force structure characterization, (ii) stochastic modeling for tactical intelligence data analysis; and, (iii) predicting and validating presence envelopes of High Value / High Priority, fixed and mobile relocatable targets (HVTs/HPTs). As highlighted in Figure 1, within the IPB Inference Ladder, our system is designed to correlate nodes to units and units to situations. Specifically, we focus on HVTs/HPTs that cannot be geolocated by the direct exploitation of any single, automated intelligence data collection asset, such as Imagery Intelligence (IMINT), or Signals Intelligence (SIGINT), or be determined from an initial set of enemy force elements sightings. This problem is extremely challenging due to typical skewness in the density of intelligence collection assets, and/or hostile weather/foliage/terrain conditions in the theater of interest Rapidly changing battlefield conditions, camouflage countermeasures, and innovative tactical strategy by the enemy commander, can only further exacerbate CRT acquisition. Only in the simplest case, one has to deal with situations where known, but camouflaged CRTs are sought, explicitly. More often, one faces inadequate knowledge about CRT classes (e.g., TELS, MELS) and CRT numbers actually present in the theater of interest. Their presence must then be inferred from limited sightings of enemy equipments/units and associated facilities. Our methodology entails synergistic exploitation of ground-based, airborne and spaceborne IMINT/SIGINT assets, for infering the presence of, detecting and discriminating CRTs To this effect our approach introduces radically new paradigms in smart intelligence data analysis. Provision of such a capability, potentially, allows for major reductions in collection management overhead and intelligence asset tasking cycles.

There are three primary technical problems in developing accurate CRT geolocation prediction strategies:

- *Machine 1{()) 1"[s[711(112011$':* given the spatial, statistical and doctrinal interrelationships among different military equipment entities, determine mathematical representations that can capture the underlying relational invariances. From a computational perspective, it is essential that these intelligence data representations be immune to spatiotemporal uncertainties injected by intelligence collection assets, as well as capture the temporal dynamics of force structure evolution

- *Force Structure Characte 112(111011 (FSC) 01 Warped Subtemplate Identification:* given an arbitrary set of collected sightings (of force structure elements) characterized by their locations and signatures of associated equipment, compute an ordering of all plausible candidate doctrinal templates/TOEs, alongwith the elemental correlations to the warped "source", such that the collected data maximally satisfy constraints and conditions imposed by predefined models of military deployment.

- *Force Location Prediction (Pl,]'):* having identified, with a reasonable degree of confidence, a plausible scheme of military maneuver for the detected unit or force structure, predict likely locations of force structure elements not sighted, i.e., not included in the input source subtemplate. Furthermore, determine nearby feasible areas of movement for all elements of the force structure Estimate the geolocation

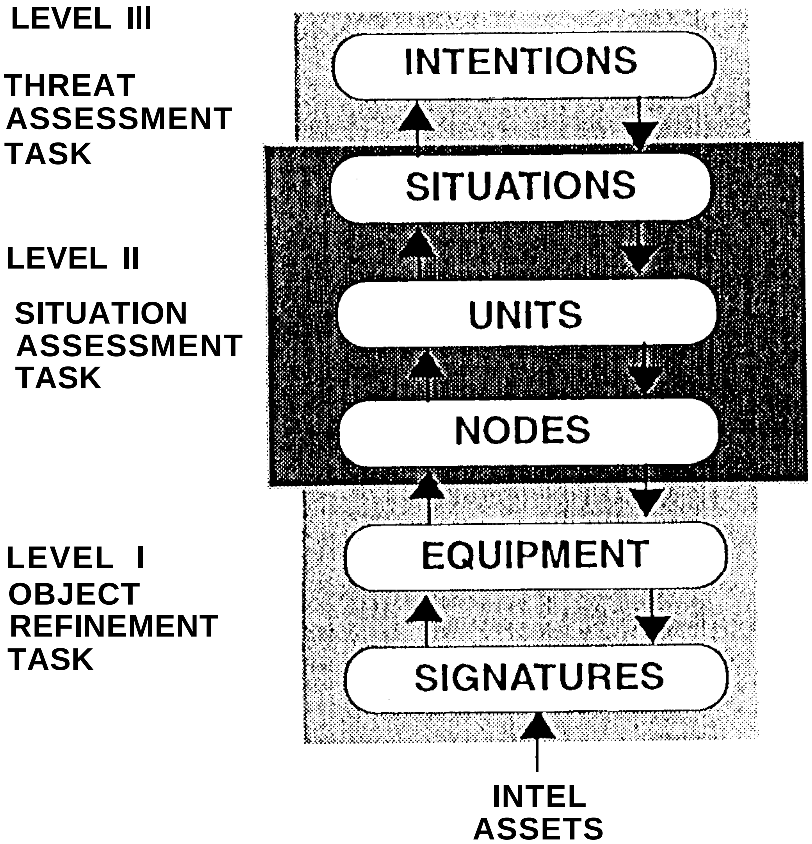

Figure 1. Intelligence Preparation of the Battlefield (IPB) Inference ladder.

manifold of constituent CRTs in conjunction with the situational semantics, including terrain, foliage and variations in enemy strategy.

The output of an automated situation assessment system that addresses the above specific problems, would be identified HVTs/HPTs and their predicted geolocation manifold. CRT presence can then either be revalidated by tasking dedicated IMINT/SIGINT intelligence assets, or directly provided 10 an interdiction tasking system. Alternately, it could be fed to tactical mobility analysis and intelligence tracking systems, for continued monitoring. Prior to this JPL effort, there was no methodology that could satisfactorily address all the above problems, or carry out even simpler computations in hard real time. Hence, in response to evolving U. S. Army needs driven by the emerging "new world order", we have formalized a powerful new tactical intelligence modeling and analysis paradigm, that combines advances in several mathematical disciplines to assess and deal with both conventional and novel tactical threats posed by broad classes of potential enemies.

II. METHODOLOGY OVERVIEW

Nodal Analysis is not a new problem for the army. It has been studied for over three decades [1,2,3], and has been a key thrust in a number of DARPA programs (e.g., ADRIES [4]), BTIs (e.g., TACNET, IES) and other DOD efforts [5]. The bulk of these programs have their methodological basis in disciplines such as artificial intelligence [e.g., rule-based systems], Graph-Theory, Neural Networks, Statistical Decision Theory, Simulated Annealing, Fuzzy logic, and Dynamic Programming.

Nodal analysis is primarily a spatio-temporal pattern matching problem. Hence, hardcoded AI rules cannot resolve the combinatorial explosion of plausible alternatives from incomplete data. A compact dynamical representation of tactical situational states is essential 10 ANA. But typical AI data structures, such as frames, or semantic nets cannot (with the exception of scripts) adequately account for OB variables such as terrain, rank attrition and tactical criticality thresholds. Also, formal AI (that includes inductive, deductive, evidential and nonmonotonic reasoning) lacks methodological tools to address the evolution of tactical situation patterns driven by hidden logic, under partially available information.

In a similar vein, representation of doctrinal knowledge with neuromorphic structures is potentially problematic. Firstly, doctrinal templates are represented on different spatial scales (e.g., ranging from less than 1 square mile to over 1000 square miles), and cannot be viewed as standardized grid-based image patterns. Secondly, neural networks can encode the impact situational parameters (e.g., terrain, weather contexts) only a priori, i.e., terrain features become part of the encoded template. Past experience with TACNET [5], that suffered from similar limitations, has shown that this severely constrains system deployment in different theaters of interest. Furthermore, neural networks cannot currently learn, in reasonable time, invariances embedded in large spatial databases of high-dimensional templates. The key limitation of neural networks is however their inability to deal with high degrees of information incompleteness. For accurately recognizing a source doctrinal template, neural networks, implemented as associative/hetero-associative memories, require as input a large fraction of the pattern (typically over 80 percent). Such a requirement cannot be satisfied in military reality. In general, only 20 to 40 percent of the force structure elements may be sighted and available for input to the force structure characterization system. Previous experience indicates that in such cases the problem of smartly assigning defaults (i. e., "force element sightings as initial conditions") is harder than the primary force structure template characterization problem.

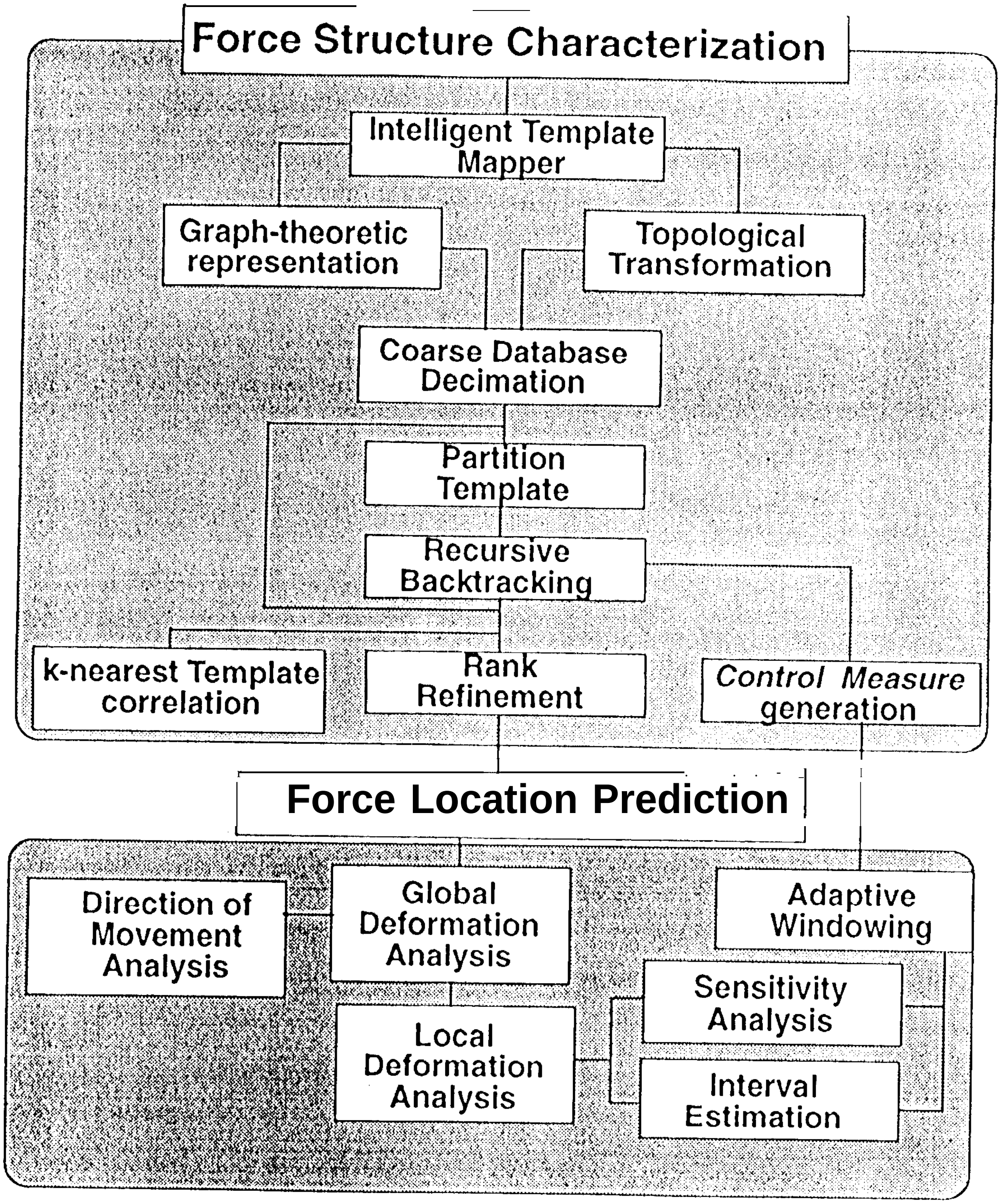

Figure 2: Overall system schematic

The overall system architecture is summarized in Figure 2. A hybrid computational approach has been adopted, that combines elements from various mathematical disciplines such as graph/hypergraph theory, neural networks and geometric probability theory.

111. EXTRACTING DOCTRINAL TEMPLATE INVARIANTS

A key component of the ANA system is the selection Of appropriate machine representations that can encode the invariances characterizing various schemes of maneuver for different force structures. In particular, representations are sought that can uniquely and compactly capture the invariances embedded in each force structure template. In the sequel, we treat each scheme of maneuver (e. g., attack, defense, pursuit, withdrawal, etc.) corresponding to a force structure (e. g., Motorized Rifle Division [MRD]) as a unique doctrinal template. The strategy we have chosen for encoding doctrinal templates entails transforming the template to a domain, in which the underlying morphological and topological relationships between the different force elements can easily be extracted.

3.1. Computing Morphological Invariants

We begin by recalling a number of basic definitions. Additional details can be found in standard texts on discrete mathematics [6].

Isomorphism. Given a pair of templates T_1 and T_2, an isomorphism is a one-to-one mapping ϕ from the elements of T_1 onto the vertices of T_2, such that ϕ preserves adjacency and non-adjacency of the force elements

Row Characteristic Matrix : An $N * (N - 1)$ matrix **R** such that the element r_{im} is the number of vertices which are a distance m away from vertex v_i.

Column Characteristic Matrix: An $N * (N - 1)$ matrix **C** such that the element c_{im} is the number of vertices from which vertex v_i is at a distance m.

Characteristic Matrix: An $N * (N - 1)$ matrix **X** such that the element x_{im} is the string concatenation of corresponding elements r_{im} and c_{im} .

Characteristic Vector: An N vector x such that the element x_i represents a row of the Characteristic Matrix X.

Furthermore, our methodology exploits two well known theorems in extremal graph theory:

Theorem 1: If **G** is an N- vertex realization of a distance matrix, **1),** then G is unique

Theorem 2: If two force structure elements v_i and v_j are partitioned into separate classes by a degree sequence, they will also be partitioned into separate classes by the characteristic vector.

Template encoding into an algebraic representation appropriate for automated nodal analysis can then be carried out in the following manner:

[1] Choose an adjacency envelop radius, to convert doctrinal and warped templates into directed graphs. Label all edges by the Euclidean distance between their terminal vertices (force structure elements).

[2] For every doctrinal template of interest, ^iT in the doctrinal database,

use Floyd's/ Djikstra's All-Pairs Shortest Path Algorithm [6] to compute the distance matrix $^i\mathbf{D}$, corresponding to the graph-theoretic shortest path between every pair of vertices;

determine the adjacency matrix, $^i\mathbf{A}$;

Using distance and adjacency matrices, compute the row and column characteristic matrices, $^i\mathbf{R}$ and $^i\mathbf{C}$ of the graph;

Compose the corresponding rows of $^i\mathbf{R}$ and $^i\mathbf{C}$; to determine the characteristic matrix $^i\mathbf{X}$

[3] Similarly compute ^0R, ^0C and ^0X for input "warped" subtemplate ^0T.

In addition to compactly capturing the spatial manifestations of military hierarchy, that are independent of the theatre of deployment, the Row-Column (RC) characteristic matrix representation is attractive for analyzing the temporal evolution of force structures, such as attrition impact and regroupings. It can be used for telescoping into substructures within a force structures, at various levels of resolution Also, from an implementation standpoint, the matrix form of representing spatial organization is highly advantageous for subsequent development of parallel algorithms.

3.2. Computing Topological Invariants

In order to resolve spatial uncertainties, our methodology exploits results from stochastic integral geometry [7] and geometric probability theory [8]. Topological (geometric) measures are constructed to rapidly identify and capture invariances underlying force element organization within a force structure, in particular the flexibility in spatial placement (doctrinally allowed, min-max spatial elasticity between two force elements). In particular, we seek a *measure* for each force structure template, that is invariant to spatial placement of elements during warping transformations. Let ζ denote the set of all possible warping transformations. For the FSC problem, it is sufficient to limit ourselves to measures which can be expressed by multiple integrals of the form

$$m(\mathrm{V}) = \int_{\mathrm{V}} f(v)\, dv \qquad (3.2.1)$$

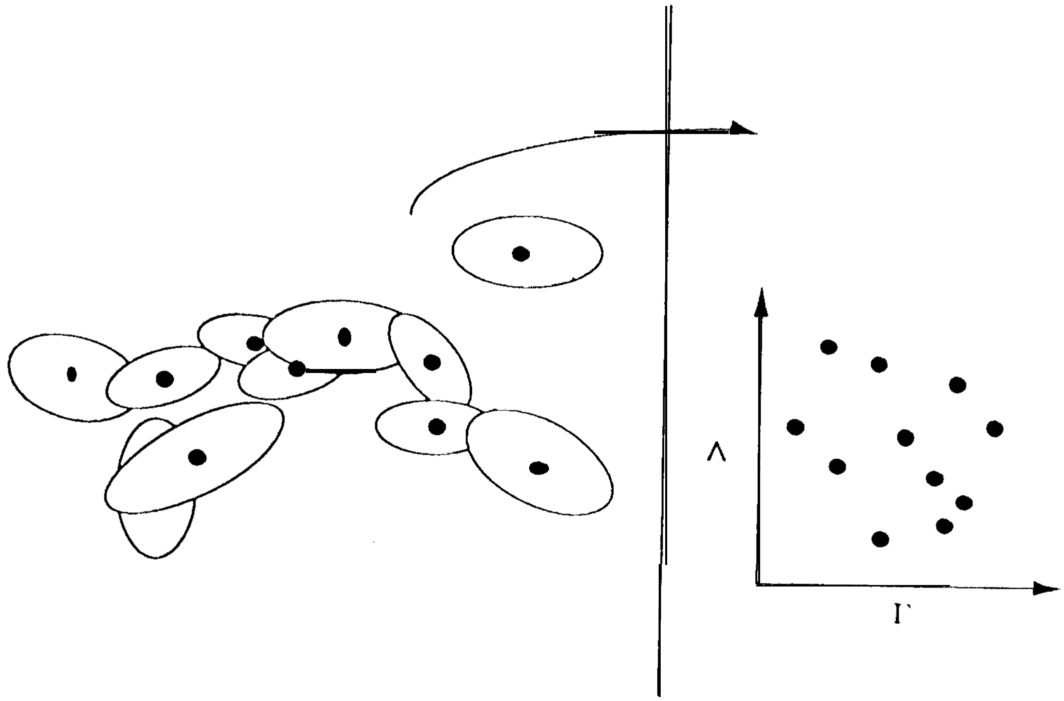

Figure 3. Overlapping Disk Separation

where V denotes the set of force elements in a force structure. In other words, we seek to determine the function $f(\mathbf{v})$ under the condition that $m(\mathbf{V})$ should be invariant with respect to ζ. Also, upto a constant factor, this measure is the only one which is invariant under the group of motions in a plane. In principle, we derive deterministic, analytical transformations on each force element, that map error-elliptic probabilities (EEP) defined on $\Re^2$ (the two dimensional Euclidean space) onto measures defined on $\Re$.

Such a representational uniqueness facilitates the rapid decimation of the search space. It is implemented by instantiating a filter constructed using measure-theoretic arguments. The transformation under consideration has its theoretical bases in the *Palm Distribution Theory* [8] for point processes in Euclidean spaces, as well as in a new treatment of the problem of probabilistic description of "typical elements" generated by geometrical processes. The latter can be reduced to calculation of intensities of *point processes*. Recall that a point process in a product space E x F is a collection Of random realizations in that space, represented as $\{ (e_i, f_i), \mid e_i \in E, \ f_i \in$ I"}.

The *Palm distribution*, II of a translation (T_n) invariant, finite intensity, point process in $\Re^n$ is defined to be the conditional distribution of the process. The importance of the Palm distribution is rooted in the fact that it provides a complete probabilistic description of a geometrical process

The Palm distribution can be expressed in terms of a Lebesgue factorization of the form

$$E_P N^* \ , \quad \mathbf{A} \ L_N \ \mathbf{X} \ \Pi \tag{3.2.2}$$

where **A** and II completely and uniquely determine the source distribution P of the translation invariant point process. **Also,** $E_P N^*$ denotes the first moment measure of the point process and L_N is a probability measure.

Thus, we need to determine Λ and II which can uniquely encode the force structure template. This is achieved by solving an appropriate set of equations involving Palm Distributions of stochastic point processes in $\Re^n$.

Qualitatively, a Palm distribution can be envisioned as describing the packing process of non-intersecting flexible "balls", which otherwise do not interact. The "template transformation algorithm" then denotes a procedure whereby one attempts to place a ball in the abstract space under consideration, such that placing of a new ball does not effect other balls. The process is graphically depicted in Figure 3.

In order to determine Λ and II, we have implemented the following algorithm (measure-theoretic filter):

[1] A: using force element Min-Max EEPs, marginal density functions are computed by projecting the uncertainty distributions associated with an EEP along the straightline connecting pairs of force structure elements.

[2] The equation $\Pi = \Theta * P$ is solved, where II denotes the T_n - ii]\'tlliiillt;:lll{l (-) rt'[lrw'[its the distribution of known point process. The above equation entails solving an inverse problem.

A number of analytical simplifications are invoked to enable the computation of **A** and II in real-time

3.3. Probabilistic Correlation Algorithm

We conclude this section by providing a summary of the correlation algorithm we developed to obtain a refined ranking of plausible template matches. These matches are obtained using the subgraph isomorphism algorithm described in Section IV.

[ ] Convert template into clusters of subgraphs using he adjacency matrix:

As shown in figure 4(a) and 4(b) use geometric transformations from projective geometry to eliminate azimuthal information characterizing the EEP. Note that EEP azimuth is merely an artifact of Level I (i.e., object assessment) sensors, and not a part of the doctrinal template. Azimuthal orientation of the EEP is eliminated by renormalizing marginal distributions of uncertainty, projecting them along the straight line connecting the centroid of force element EEPs.

[1.2] As shown in figure 5, compute the EEP for pairs of adjacent force structure elements in doctrinal templates.

[2] For all pairs of force elements within the adjacency envelop determine λ and

[3] Repeat Step [2] for all sighted force structure elements

[4] Compute ent opy of deviation of "realization" from doctrine. Sum up the deviation entropy.

[5] Perform thresholding to determine ordered anking

IV FORCE STRUCTURE CHARACTERIZATION ALGORITHM

Conceptually, the subgraph isomorphism algorithm for force structure characterization consists of two phases: (i) an initial partitioning of force elements in the "sighted" aggregation of force elements and every doctrinal template of interest, based on the degrees of vertices; and (ii) iterative heuristic algorithms, which attempt to consider the neighborhood of each respective force element, to characterize a vertex by its relationship with ever increasing numbers of more distantly connected vertices.

The overall rank-refinement algorithm is summarized in Figure 6. This iterative graph-partitioning / rank-refinement algorithm exploits *vertex color*, i.e., force element label, and *doctrinal constraints*, e.g., distortions in exemplars are limited by hard constraints (such as bounded spatial elasticity on the internode distances), to exponentially decimate (a) the number of plausible to-be-searched candidate templates of interest; and (b) the size of unresolved (uncorrelated) "source" template.

4.1 Coarse decimation of search space :

We first attempt to reject templates that significantly lack force elements types, in terms of hose present in he warped input template We proceed as follows:

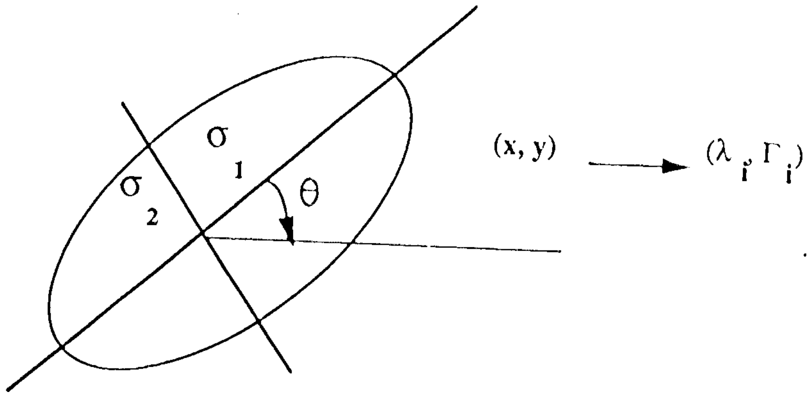

Figure 4(a). Elliptical Error Probability EEP.

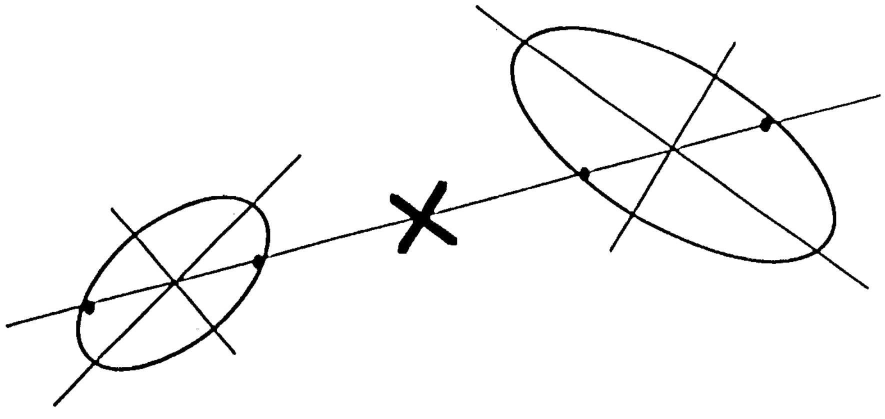

Figure 4(b). Collapsing Azimuth Information. (Projective geometry technique to desire density distribution function for interelemental distance

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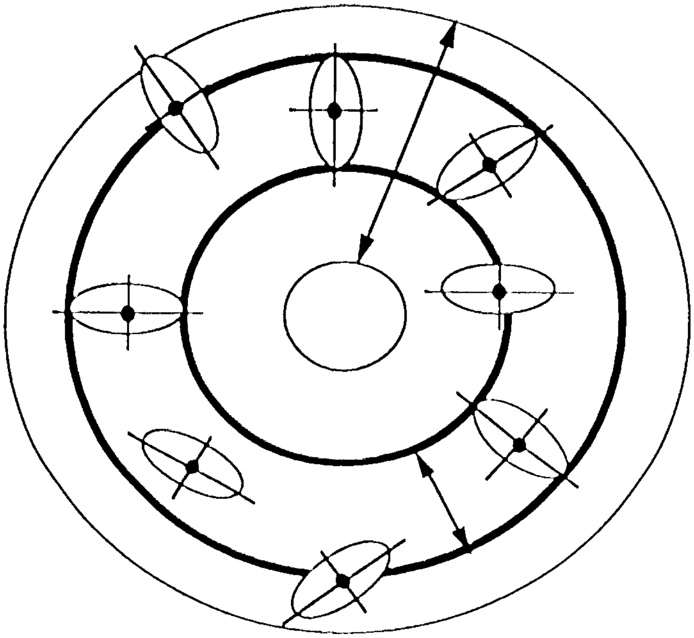
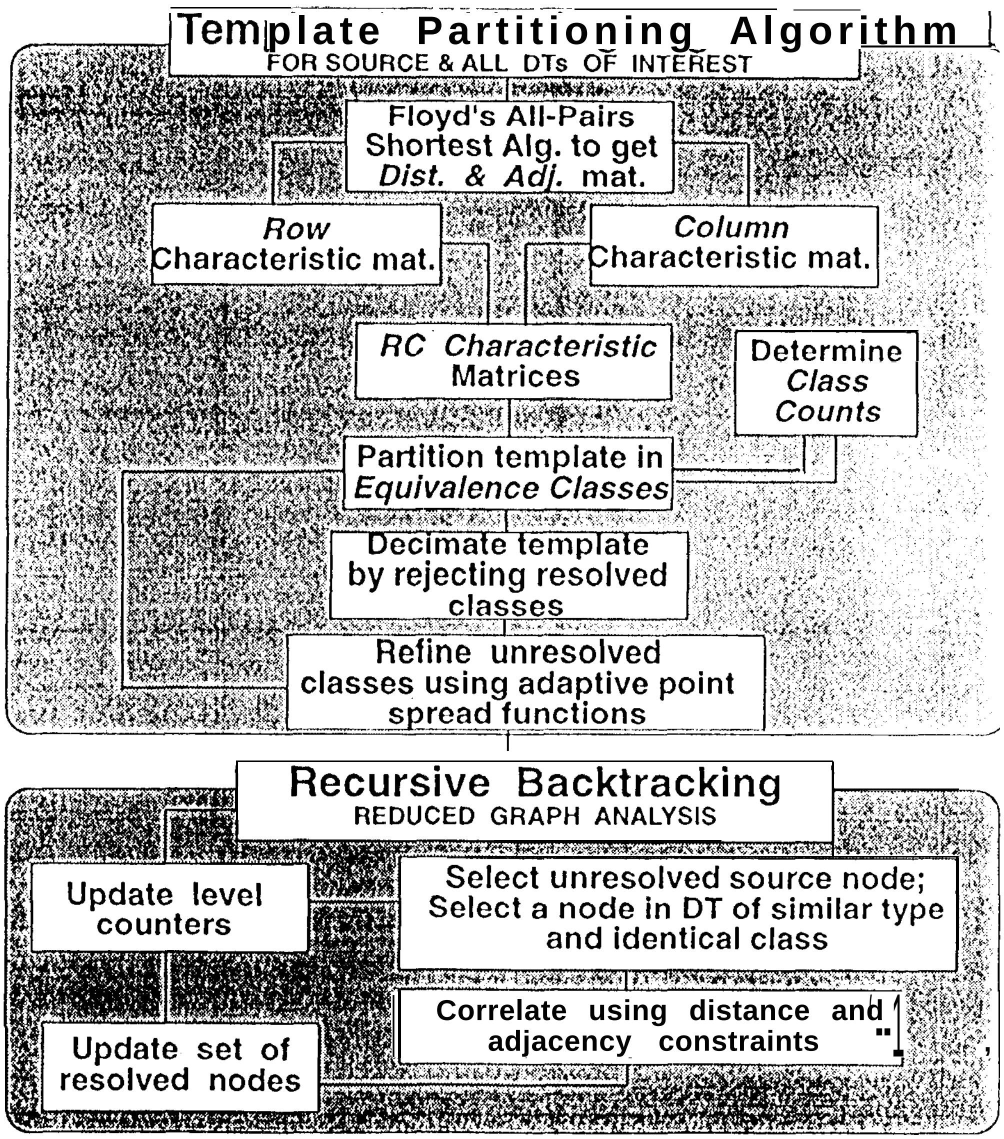


Figure 5. "corridor" of Spatial Stochasticity for force elements with pairwise infraction, (Find measure for sets of geometric objects (manifold) with the property of being invariant undergroup of transformations)

Figure 6. Pseudocode for subgraph isomorphism algorithm



The doctrinal template database is viewed as a hypergraph,

$$H = (V; T_1; T_2; T_3; \ldots, T_n)$$

where a hyperedge, T_i denotes the set of force structure elements in the doctrinal template i. Furthermore, each T_i is itself a hypergraph comprising of a forest of graphs, $T_i = (V_{ii}; t_{i1}; t_{i2}; \cdots; t_{ik})$, where V_{ii} denotes set of force elements in T_i, and t_{ik} represent the set of force elements in a connected component of T_i.

The transversal of a hypergraph is defined to be a set $T \subset$ b', such that

$$T \cap T_i \neq 0 \quad \text{for all} \quad i$$

The minimum transversal is defined by set $T \cap T_i$. The *transversal number*, $\tau(H) = \text{Min}|T|$, is defined to be the minimum number of nodes in a transversal of H. In our model, assume the warped input template, 1, to represent the minimum transversal of H.

Using a graph-theoretic algorithm proposed by Gulati, Iyengar and Barhen [9], we compute the first minimum transversal over all templates in the database and then convolve it with the input. Denoting the transversal of a hypergraph by Tr(.), the following steps are implemented.

Transversal Computation Algorithm

[1]: Determine Min $\aleph = \{H_1, H_2, , H_k\}$, where H_1, H_2, H_k denote hypergraphs obtained by partitioning the force structures into a forest of graphs

[2]: Successively determine the following families:

$\aleph_1 = \{H_1\}$ yielding Tr {If,) = ({(I} \ $a \in H_1$)

$\aleph_2 = \aleph_1 \cup \{H_2\}$ yielding Tr $\aleph_2$ = Min (Tr $\aleph_1$ V Tr { H_2 })

$\aleph_3 = \aleph_2 \cup \{H_3\}$ yielding Tr $\aleph_3$ = Min (Tr $\aleph_2$ V Tr{ H_3}), etc.

The above steps show how Tr $\aleph_{i+1}$ is obtained from Tr $\aleph_i$ If Min $\aleph$ has k members, then the above algorithm constructs Tr $\aleph$ = Tr $\aleph_k$ in k steps. This algorithm can be very efficiently expressed in terms of Boolean operations using a transformation suggested by Maghout Note also that templates with a transversal number less than $\tau(I)$ are immediately rejected as probable sources of warped input 1.

We now address the issue of point spread conflict computation for rank refinement. Our approach for rapid elimination of doctrinal templates from further consideration, is based on a severe violation of adjacency and force element type constraints. It involves enumerating the number of type conflicts over an expanding adjacency envelope Specifically, we proceed as follows:

[1] Compute geodesic for each doctrinal template;

[2] Choose initial adjacency envelope radius in terms of the input template geodesic, scaled by a factor S;

[3] Connect nodes over the adjacency envelope, to form a directed graph for the source and doctrinal templates;

[4 Compute the packing density, i.e., average number of force elements in each connected component of the graph:

- If all templates lie within 2σ of the packing density, accept optimal adjacency envelope radius, else recompute envelope radius by increasing S;

[5] For all force structure elements in the input template, ${}^{i}T$, determine the cardinality of matching adjacency sets with respect to all remaining plausible "doctrinal source" templates:

- Incrementally expand adjacency envelop to span the template graph;

[6] Rank-order templates by increasing number of matching conflicts with the input template;

[7] Eliminate all templates from the next computational phase with over 20% conflicts matching conflicts.

We now proceed with the details of the subgraph isomorphism algorithm for force structure characterization.

4.2. Subgraph Isomorphism

This algorithm, a refinement over [10] involves two passes: an initia parti ioning and a recursive scheme for correlating the unresolved force structures.

Pass 1:

Use the rows of each matrix, ${}^{i}\mathbf{X}$ to partition the force structures into equivalence asses; two nodes in ${}^{0}\mathbf{X}$ and/or ${}^{i}\mathbf{X}$ are assigned to the same equivalence class iff:

they have identical corresponding rows;

- every element of a row in ${}^{0}\mathbf{X}$ is not greater than the corresponding element in ${}^{i}\mathbf{X}$, and the two nodes have identical types;

[2] Determine class counts for all equivalence classes. Analyze to further par ition nodes into distinct classes if they belong to different node-types;

[3] Isomorphic map immediately results for identically labeled nodes belonging to the same class, but different graph, with a class count of unity;

[4] Further refine class partitions to resolve the isomorphic mapping for additional nodes;

- Expand the adjacency envelop radius to ascertain which nodes in the two templates have identically labeled sets of neighboring nodes, provided the distance constraints are satisfied;

- club such nodes in the same class;

- For the purpose of subsequent ranking, record the number of neighbor to neighbor type-violations.

Pass 2:

[5] Partition the warped input subtemplate into resolved and unresolved force struc ure elements;

[6] Reorganize the classes:

reorder the class numbers and class counts to account only for unresolved force structure elements;

deactivate edges emanating from/to resolved nodes in the adjacency matrix

[7] Execute a backtracking algorithm on the reduced graph:

[7.1] Set current level counter to 0. Set chosen vertex at current level to null;

[7.2] If current level counter equals the number of unresolved force structures, exit;

[7.3] Set chosen vertex to some unresolved vertex in the source template; mark vertex resolved;

[7.4] Choose an unresolved vertex of similar type and identical class in the doctrinal template currently under consideration;

[7.5] Correlate using distance and adjacency constraints:

- If correlation established then goto [7.6] else, if unresolved vertices emain, hen goto [7.4]; else, output vertex as resolved;

[7.6] increment level counter

[7.7] if set of unresolved vertices empty, exit; else go to [7.3]

The output from Pass 2, includes the identifier of the force structure that maximally correlates with the source template presented as input to the system, as well as the "resolved" explicit correlations between the force elements in the two templates.

V. FORCE LOCATION PREDICTION ALGORITHMS

Our next objective is to predict likely locations of force structure elements not included in the sighting (i.e., in the warped input subtemplate) from the nearest correlated "source" template, and determine nearby feasible areas of movements for all elements of the force structures. The methodology entails the identification of globally consistent, simple local template distortion strategies constrained by a window of focal attention (e.g., a "Control Measure"). Specifically, geolocation prediction involves the following key steps:

[i] adaptive generation of focal attention window, consistent with template semantics;

[ii] abstraction of a virtual transformation within the focal attention window, using a technique that combines algebraic projective geometry with a neural network model;

[iii] sensitivity analysis for prediction refinement;

[iv] interval integration algorithms for critical node geolocation and incorporation of operational constraints, e.g., terrain, elevation, weather impact.

In the sequel of this section, we first discuss our computational strategy for predicting "dropped" force structure elements, i.e., elements nominally present in the identified template, but not included in the sightings reports. Then, we address the issues of uncertainty propagation and integration Of operational constraints

5.1. Global Distortions

Simple, homogeneous transformation matrices are well known in the literature for computing the impact of Euclidean transformations, e.g, rotation, translation, scaling, and combinations thereof, in two and three dimensions. Using the correlated warped and doctrinal force structures, we can readily determine the parameters of the distortion transformation matrix. Furthermore, distance constraints and the nodal uncertainty envelopes in the doctrinal template can be used to generate "presence" envelopes for the dropped force structures. Global force structure warping is mainly relevant to strategic battlefield analysis.

5.2. Local Distortions

A key assumption made here is that a warped template satisfies some "continuity" conditions in terms of local deformations. The unwarping problem can then be stated as follows. Given the coordinates of sighted force elements, and the coordinates of the corresponding doctrinal elements, determine the elements of an affine virtual transformation A, such that

$$\mathbf{A} \cdot \mathbf{Q}_d = \mathbf{Q}_r \qquad (5.2.1)$$

where $\mathbf{Q}_d$ and $\mathbf{Q}_c$ denote the $3 \times M$ matrices of homogeneous planar coordinates of M doctrinal and corresponding sighted force elements respectively. The affine transformation, $\mathbf{A}$ is assumed to be of the form,

$$\begin{pmatrix} A_{11} & A_{12} & A_{13} \\ A_{21} & A_{22} & A_{23} \\ 0 & 0 & 1 \end{pmatrix} \tag{5.2.2}$$

In other words,

$$\begin{pmatrix} x_{c,m} \\ y_{c,m} \\ 1 \end{pmatrix} = \begin{pmatrix} A_{11} & A_{12} & A_{13} \\ A_{21} & A_{22} & A_{23} \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x_{d,m} \\ y_{d,m} \\ 1 \end{pmatrix} \qquad m = 1, \cdots, M \tag{5.2.3}$$

Since different areas of the template are assumed to be impacted differently, a window of attention is needed to limit the scan space. A minimum of three points is required to predict a missing force element within the window of attention. Initially known pairs, q_d and q_c are used to learn the transformation matrix, $\mathbf{A}$, where

$$\mathbf{A} = \mathbf{Q}_c \cdot \mathbf{Q}_d^T \, (\mathbf{Q}_d \, \mathbf{Q}_d^T)^{-1} \tag{5,2.4}$$

we can write

$$\mathbf{A} = \mathbf{Q}_c \cdot \mathbf{B} \tag{5.2.5}$$

with

$$\mathbf{B} = \mathbf{Q}_d^T \, (\mathbf{Q}_d \mathbf{Q}_d^T)^{-1} \tag{5.2.6}$$

Our current implementation, exploits artificial neural networks, to learn the virtual transformation **A.** The "learned" transformation matrix is then applied to predict coordinates of dropped elements.

Specifically, the neural network requires as inputs the warped subtemplate, the "nearest" doctrinal template, and, force structure correlations output by the isomorphism algorithm. It provides as output the parameters of the distortion transformation matrix. The remainder of dropped elements can then be predicted using the relationship

$$\mathbf{Q}_p = \mathbf{A} \quad \mathbf{Q}_d \tag{5.2 7}$$

5.3. Uncertainty Propagation

It is clear from the equation $\mathbf{A} = \mathbf{Q}_c \cdot \mathbf{B}$ that any perturbation in the values of $\mathbf{Q}_c$, i.e., $\delta\mathbf{Q}_c$ will be propagated via the matrix B to the values of the transformation matrix $\mathbf{A}$. Therefore we can write

$$\delta \mathbf{A} = \delta\mathbf{Q}_c \cdot \mathbf{B} \tag{5.3.1}$$

The sensitivity of each element of the computed transformation matrix A with respect to the m-th sighted force element coordinates, $x_{c,m}, y_{c,m}$, can easily be calculated via,

$$\frac{\partial A_{i,j}}{\partial x_{c,m}} = \frac{\partial A_{i,j}}{\partial y_{c,m}} = B_{m,j} \tag{5.3.2}$$

Assuming equal probabilities for each sighted force element (equal importance weighting), the overall uncertainty in the calculated values of the transformation matrix, **A** with respect to the uncertainty of the sighted values is given by

$$\Delta A_{1j} = \frac{1}{M} \sum_{m} | \mathbf{B}_{m,j} \, \Delta x_{c,m} | \quad (5.3.3)$$

$$\Delta A_{2j} = \frac{1}{M} \sum_{m} | \mathbf{B}_{m,j} \, \Delta y_{c,m} | \quad (5.3.4)$$

The uncertainty in the predicted points can then be computed using te uncertainty values ΔA_{ij}, and the doctrinal force elements coordinates

$$\Delta x_p = \sum \Delta A_{1j} \cdot x_{dj} \quad (5.3.5)$$

$$\Delta y_p = \sum \Delta A_{2j} \cdot x_{dj} \quad (5.3.6)$$

When we use ac ditional unc ertainties, which often stem from doctrinal coordinate elasticity, much more complex formul as arise.

5.4. Operational Constraints and Predicted Manifold Refinement

We now focus on refining the prediction manifold by integrating operational constraints. It addresses the issue of overlapping and possibly conflicting distortion-factors, generated by the different processing windows. Our approach is derived from ideas based on Marzuello's "Interval Integration Algorithm" proposed for multisensor fusion using hierarchial distributed sensor networks [1 1] and improved by Prasad et al [12,13]. In summary, the methodology entails transforming an uncertain real-valued constraint, to a uniform interval $[a,b]$. The eve*-la~,l)illg intervals are then combined, and propagated to obtain a best estimate of the true value, along the hierarchy of constraints. In applying this method, the const rain it (e .g., terrain feature, weather pattern, etc. .) is assumed to be distributed uniformly ove r t he interval

Let the force element geolocation manifold, GM, be subject to S' abstract constraints (doctrinal, weather, terrain, etc.) , C constraints of critical interest, and L be the number of force elements in the window of attention that were used in predicting the in it ial manifold, such that $L = \{S_1, S_2, , S_n\}$. Let t he abstract interval estimate of S_j, for $1 \leq j \leq n$, be denoted by $I_j = [a_j, b_j]$ with endpoints a_j and b_j. The constraint satisfaction meth od is based on an algebra of Heaviside funct ions Let interva s', $I_1, I_2, \cdots, I_n$ have the characteristic functions $\chi_1, \chi_2, , \chi_n$ respectively. The characteristic function, χ_j of the j-th constraint S_j is define d as:

$$\chi_j[x] = \begin{cases} 0, & \forall \; x < a \\ 1, & \forall \; x \geq a \end{cases}$$

i.e., $\chi_j : \Re \longrightarrow \{0,1\}$, and

$$\chi_{j[a,b]}\,[x] = \chi_{ja}[x]\,(1 - \chi_{jb}[x])$$

The problem is the integration of the intersection region I_j to obtain "reliable" and "fairly accurate" estimate of the geolocation manifold. Further, we require

$$||f|| = \sup\{|f(x)| \mid x \in \Re\}$$

i.e., $||f||$ denotes the smallest real number α such that $f(x) \leq \alpha \;\forall\; x$. Also, we define the concepts of support and overlap of f as:

$$\mathrm{Supp}\{f\} = \{x \mid f(x) \neq 0\}$$

$$O(x) = \sum_{j=1}^{n} \chi_j[x]$$

where the latter refers to the number of overlapping intervals which satisfy the constraint at any geolocation (coordinates expressed by the tuple G(l,m), where l,m refer to the latitude and longitude, respectively) denoting the area of interest.

The maximum number of intersecting intervals, or region of maximal constraint satisfiability in which any geocoordinate satisfies $G(l, m) \in f_i$ is then given by the integer $||\chi_i O||$. The latter expression, in effect computes the $||\chi_i O||$-clique. Recall that an n-clique denotes a group of intervals having a common intersection

Also, the following results hold,

$$I_i \cap I_j = \chi_i(x)\,\chi_j(x)$$

$$\chi_{\cup I_i}[x] = 1 - \prod_{i=1}^{n} (1 - \chi_i[x])$$

However, the maximally overlapping interval (as per the above definition) I_p contains points which do not belong to intervals $\mathrm{Supp}\{S(x)\}$ where,

$$\mathrm{Supp}\ \{,\$'(\$)\} = \cup_{i=1}^{k} L_i$$

where $L_i = [\alpha_i, \beta_i]$ with $\beta_i < \alpha_{i+1} \forall 1 \leq i \leq k-1$. An evaluation of the L_i's is performed to attach a weight to each of them and then choose those $L_i's$ with maximum weight to be the interval containing the correct physical value. We then again embed these $L_i's$ of maximum weight in the smallest possible interval and take it to be the output estimate. Thus, for the operational constraints integration problem, L_is denote a weighting function, such that each L_i corresponds to the likelihood of containing the correct geolocation Also, let $\chi_{L_i}(x)$ be the charateristic function of I_p. Then we can define the "popularity" function of the j^{th} constraint as

$$P_j = \sum_{k=1}^{n} ||\chi_k \quad \chi_j|| - 1$$

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where $\|\chi_k\ \chi_j\|$ denotes the number of intersecting intervals.

To increase the geolocation accuracy, we introduce a measure, denoted $\omega(L_i)$, in terms of as the sum of popularities of all overlapping intervals involved in the formation of L_i, i.e.,

$$\omega(L_i) = \sum_{j=1}^{N} \| \chi_i \chi_j \| P_j$$

The popularity function yields the $(n - f)$th-or-more clique. Let $r = \max\{r_i \mid 1 \leq i \leq k\}$, $m = \min\{i \mid r_i = 7'\}$, and $M = \max\ \{i \mid r_i = r\}$. Then the "narrowest" geolocation, i.e., integrated output estimate is

$$I_{P^\bullet} = [\alpha_m, \beta_M]$$

Thus, if there are n constraints, and f non-intersec ing constraints, the $n - f$ over apping intervals are given by

$$S(x) = 1 - \prod_{j=1}^{n} (\quad \chi_{[n-f,\infty)} \ \|\chi_j 0\| \ \chi_j[x])$$

where $\chi_{[n-f,\infty)}$ is the characteristic function of the interval $[n - f, \infty)$. Note that

$$\chi_{[n-f,\infty)} \ \|\chi_j O\| \ \chi_j[x] = \chi_j[x]$$

So, if and only if, I_j has $n - f - 1$ intersecting intervals, the estimated interval containing Supp$S(x)$ is given by

$$I_p = \left[Min\{x \mid S(x) = 1\},\ \text{Max}\{x \mid S(x) = 1\} \right]$$

and I_p yields the geolocation manifold for each dropped element. For a detailed analysis the reader is referred to **[12,13]** and references therein.

VI. Conclusions

The automated nodal analysis system presented in this report is particularly attractive for tactical intelligence analysis. Its enabling computational features can be summarized as follows:

- 1?1(/()1 *ndent of doctrine source*. our methodology is uniformly applicable to Iraqi, Russian, N Korean, Brazilian or Chinese doctrinal templates;

- *Robustness in the presence of limited information availability:* it has been tested with warped subtemplates containing as little as 20 percent of the force structure elements present in a template;

- *Capability spectrum :* The system can handle distortions of arbitrary type and magnitude;

- The methodology is *coordinate independent:* templates can be on different spatial scales;

- o The system is *terrain independent:* terrain is not used in the force structure characterization process, it is only used for geolocation prediction;
- o *Scalability:* the methodology can easily be extended to include situational parameters such as tactical criticality factors, spatial constraints (e. g., terrain) and doctrinal constraints (e. g., explicit hierarchies);
- o *Computational efficacy:* our benchmark tests have yielded a response time to within a minute on a SUN/4 equivalent (40 MIPS) processor, for up to 100 force structure templates with 10-100 force structure elements per template.

In summary, for the ASAS Program Office TechBase thrust on Automated Nodal Analysis, JPL has chosen to address a problem of major applicational significance to the US Army, i.e., Critical Relocatable Target (CRT) identification and geolocation. This problem coalesces two issues fundamental to tilt' development of Reconnaissance, Surveillance and Tactical Assessment (1/ S'I'A) technology: enabling real-time capability for in-situ processing of tactical intelligence data, and developing a paradigmatic framework amenable for implementation on computational platforms ranging from surveillance satellites to ruggedized workstations. Enabling conceptual and computational formalisms are developed, that synergistically exploit limited sensor sightings of associated facilities/equipment and logistics supply train, terrain features, Order of the Battle (OB) knowledge, and weather impact on *a priori* known mobility characteristics of a force entity, to predict presence envelopes for CRTs.

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