EVIDENTIAL REASONING FOR GEOGRAPHIC EVALUATION FOR HELICOPTER ROUTE PLANNING

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Evidential Reasoning for Geographic Evaluation for Helicopter Route Planning *

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Abstract

In order to plan operations where knowledge of significant elements is imprecise and uncertain, a means of characterizing the situation in terms of the various factors that may influence those operations must be provided. In this paper we discuss an approach to that characterization that uses evidential reasoning to handle the uncertainty, imprecision, and incompleteness typical of sources of real-world information and knowledge, to support planning routes for military helicopters.

Evidential reasoning is a maturing collection of inference techniques for reasoning with uncertain information. Based on the Shafer-Dempster theory of evidence, evidential reasoning uses a non-Bayesian updating scheme to combine evidence provided by multiple, diverse knowledge sources. Knowledge sources in an evidential reasoning system are not required to attribute their belief to a universe of discourse comprised solely of mutually exclusive, exhaustive, singleton events, as required by a classical probability approach. Rather, they may express levels of ignorance explicitly by allocating belief to disjunctions of propositions, thereby leading directly to an interval measure of belief; ignorance is expressed by the width of this interval.

Evidential reasoning evolved from consideration of appropriate models for reasoning about information acquired from sensors, and therefore seems natural for drawing conclusions from sensor data and prestored maps regarding the degree to which a selected geographic area will support certain activities. Here, we discuss evidential reasoning and illustrate the utility of the technology for classifying geographic areas by describing our current map-and-sensor-based research in which we estimate the utility of land areas for concealing helicopter operations.

1 Introduction and Overview

Developing strategies to achieve some future aim is a significant human activity. In most "real-world" situations, such planning activities must be carried out using information of

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varying degrees of reliability, precision, and completeness. The construction of automated planning systems demands that automated techniques be developed for representing and using such information, while at the same time controlling the generation and search of the potentially huge search spaces that can be created. In our current work we are addressing the problem of route-planning for U.S. Army helicopter pilots flying at extremely low altitudes (e.g., nap-of-the-earth or NOE, literally at or below the tops of the trees), where effective plans for achieving mission goals must be derived, even under conditions of uncertainty and ignorance regarding locations and strengths of possible hostile troop concentrations, the availability of landmarks for navigation, and the suitability of the terrain for tactical maneuvers such as masking. In order to have any hope of developing effective plans, a system must be able to characterize the situation as accurately as possible.

1.1 The Mission-Planning Context

Although this paper addresses only the initial characterization of an area of interest, the context of that analysis and its rationale are important to the overall understanding of the methodology, and are described here. We have several system goals for our ultimate implementation. The primary goal is that under the interactive guidance of the human user, the system be able to capitalize on the full variety of information (such as aerial photographs, maps, factor overlays, intelligence reports, tables of organization, and characteristics of sensors and weapons) typically available to a mission-planner. A second requirement is that a component of the system must be capable of running on computational equipment within the helicopter, in order to follow the execution of the plan enroute and, when necessary, to replan parts of the mission.

The first goal is addressed by combining a system for reasoning from evidential information, Gister,[1] with ImagCalc, a system for efficiently manipulating imagery of various types. The basic mode of operation will support a user who provides high-level information regarding the appropriate sources of primitive information and their manipulation, to derive mission-significant factors. The user will, in effect, detail a prototypical analysis of available information, which will be compiled into code that will be run directly over map and image descriptions of the area of interest, to describe the area in mission-related terms.

The second goal will be addressed by deriving a compact graph representation of the area of interest, which may be used enroute to derive alternate routings when it is necessary to deviate from the primary plan. This representation will encode salient properties from the original characterization, but will require neither the full original knowledge sources nor the elaborate computational machinery necessary to produce and evaluate the initial characterizations.

Our basic approach to the complete planning problem is first to partition the area of interest into a collection of "local areas." These local areas (which may range from the size of "pixels" in the original images or maps to much coarser resolutions) are then characterized on the basis of *local* measures (which may, of course, be a function of situations and events external to the local area itself) according to how well necessary helicopter operations

[1] **Gister, Grasper II and ImagCalc are all trademarks of SRI International.**

may be supported in that area. Similar adjacent local regions will then be clustered until a reasonable number of regions of significant size are created. Within each region, all paths are to be considered equivalent, thereby enabling the planner to focus on qualitatively different routes. A graph (essentially the dual-graph of the collection of regions) will then be derived from the resulting clusters, and a heuristic search procedure used to select candidate routes through the graph. These candidates may then be evaluated based on their *route* properties (i.e., those properties that are route-dependent, such as fuel used or total exposure) as well as the local area properties. If acceptable candidates are found, they will be ranked and presented to the user; if not, certain predefined constraints may be relaxed, and a new attempt made. If, after several iterations, no acceptable routes are determined, the user will be required to change his criteria or their relative weightings, or to accept routings of inferior quality to that originally requested.

The development of the complete system is ongoing, however, each of the individual steps has been successfully addressed. In the remainder of this paper, we discuss just the characterization stage of the process and describe how the user can specify and test knowledge structures for analyzing and describing geographic areas before applying them to the available geographic data. This approach capitalizes on the capabilities of Gister and ImagCalc. Both of these systems were developed at SRI and currently reside on the Symbolics 3600 family of Lisp machines.

1.2 The Use of Evidential Reasoning to Characterize Local Geographic Areas

The process of characterizing areas of interest on a map begins with a mapping from measurable properties into *belief functions*, which describe the degree to which those properties might affect intended operations. Belief functions (described in detail below) are provided by *knowledge sources* (KSs) and represent their view of the state of the world. A unit of *belief* (relative likelihood) is distributed over a set of propositions or statements describing possible states of the world. The set of possible propositions over which a KS may distribute its unit of belief is the set of all subsets derived from the *frame of discernment*, a set of mutually exclusive, exhaustive, primitive propositions (typically referred to as Θ). More general than classical Bayesian probability distributions, belief functions, also known as *evidential mass functions* (or, more simply, *mass functions*) may distribute their unit of belief over overlapping (i.e., nonexclusive) propositions. In particular, a knowledge source may indicate ignorance (or imprecision) by providing a mass function that distributes belief over a disjunction of propositions, without providing a detailed distribution of belief to elements of the disjunction. Allocating an amount of belief directly to Θ indicates complete ignorance to that extent. As belief allocated to disjunctions may eventually devolve to any of the individual propositions, their relative likelihoods are constrained to fall within an *evidential interval.*

Using evidential reasoning to characterize geographic areas offers several benefits. The primary advantages are related to a knowledge source's ability to state precisely what it knows about a situation, without being forced to artificial precision by the mathematical requirements of standard probability theory. In particular, the theory does not require the knowledge or use of prior probability distributions, which are usually extremely difficult to determine (although when prior information is available, it is easily used). The formal theory underlying evidential reasoning (described below) makes it straightforward to construct the underlying knowledge structures needed for analysis, and then to construct the corresponding analyses using a variety of evidential reasoning operators (such as fusion, translation, and discounting) to interpret real-time information.

Characterizing geographic areas to support tactical operations necessarily entails drawing conclusions and making statements of varying degrees of precision and reliability. For example, to the helicopter mission planner, an important characteristic of a geographic area might be the degree to which it is likely to offer opportunities for a helicopter to hide (i.e., to become *masked*) from hostile eyes (or sensors). This opportunity may at best be estimated based upon the type of terrain and ground cover likely to be found in the area in question. Forcing any particular source of knowledge about the situation to make precise estimates is (usually) to force a false, unsupported precision into the computations. Instead, it is better to let the various KSs provide their input at a degree of precision commensurate with their knowledge, and then to look for a consensus among several sources.

1.3 The Derivation of Belief Functions for Helicopter Mission-Planning

A variety of information and preprocessed data comprises the information sources for characterizing geographic areas and evaluating subsequently chosen routes. These information sources include direct statements about the current situation as well as statements that may be inferred independently of the helicopter's activities. The general types of information currently expected to be contained in the mission-planning system include: platform state (i.e., location, velocity, height, resources, and sensor signature), goal information, terrain attributes (i.e., vegetation, contour, terrain type, topography, and cultural features), meteorology (i.e., weather and visibility), navigational landmarks, hostile forces (locations, types, sensors, and weapons), and control data (e.g., refueling points and flight corridors). A digital terrain map (DTM) over a typical area of interest (actually of Yosemite National Park, California) is shown in Figure 1. In this figure lower elevations are shown as lighter shades. The crosses correspond to the specified locations of hostile observers (and are used in computing the intervisibility map of Figure 2. Alongside the DTM is shown a wire-frame model of the area from an oblique perspective southwest of the Valley.

In these experiments, we used a Level-7 DTM (with a resolution of approximately 120 meters per pixel) as the base representation, along with a registered overly describing vegetation. The original data was sampled using a 4x4 pixel patch to produce local areas of approximately 480 meters square. The sampling method varied for each type of characteristic: for TOPOGRAPHY, we used the variance of the altitudes within the patch as the pixel value; for VEGETATION, we averaged the vegetation types; and for INTERVISIBILITY we selected the minimum safe height in the patch. After sampling the data, they were mapped into the appropriate belief functions. These belief functions were used to determine the ultimate value of RISK for each location.

As an example of how a belief function may be derived from information about the world, consider the problem of determining the maximum safe altitude for undetected helicopter

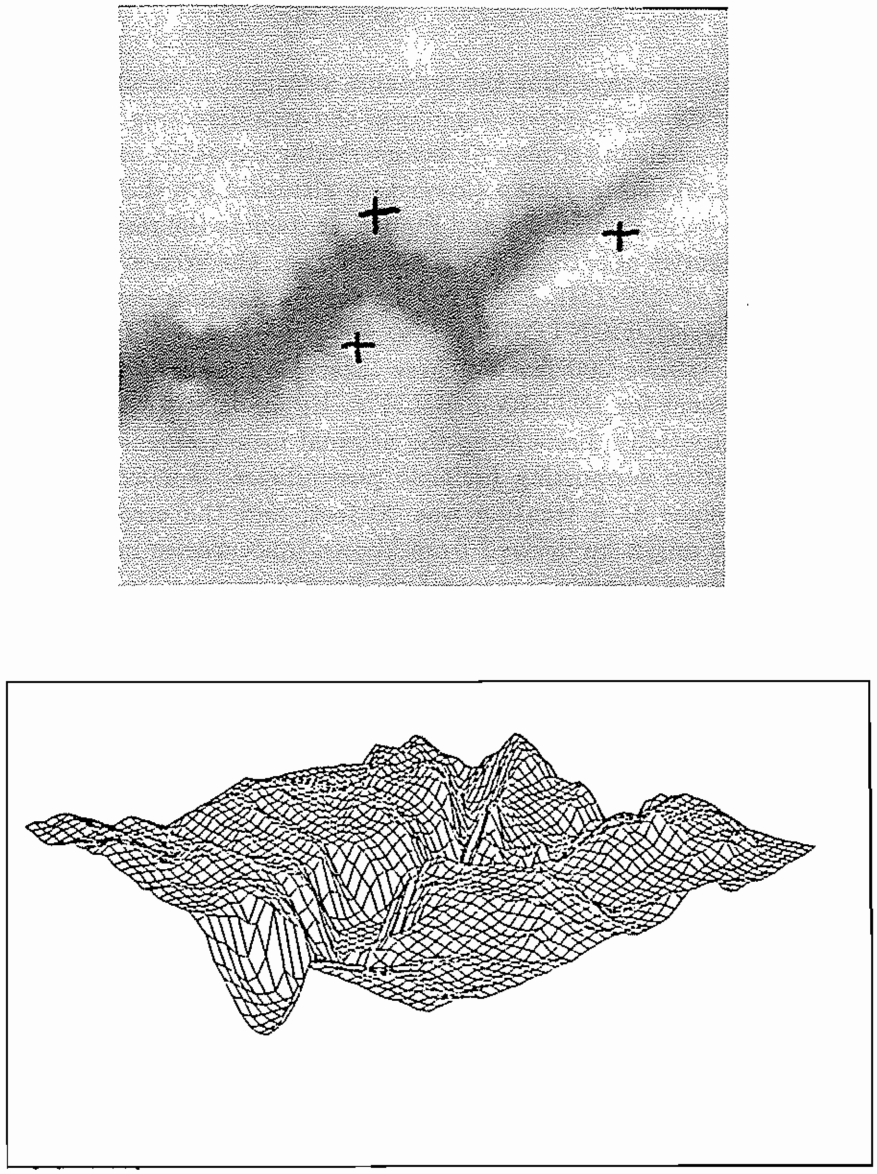

Figure 1: A DTM (a) over Yosemite (lower altitudes shown as darker points) With a Corresponding Wire-Frame Model (b) of the Area.

operations. From information regarding the probable locations of hostile forces (as shown in Figure 1), we may compute an ***intervisibility map*** of the area depicting the maximum height above ground level that a helicopter may fly before risking exposure to those forces. Figure 2a shows the original intervisibility map (lower safe altitudes are shown as lighter areas); the sampled map is shown in Figure 2b; and Figure 2c depicts the resulting belief function quantized into the categories of MINIMUM HEIGHT (i.e., the area is viewable all the way down to the ground), NAP-OF-THE-EARTH (the area is viewable down to approximately 15 feet above ground level), CONTOUR (15-40 feet), LOW-LEVEL, (40-200 feet), and ABOVE-LOW-LEVEL (above 200 feet). These intervals represent the basic statements in the frame of discernment for INTERVISIBILITY. By associating an error interval with the measured value (essentially discounting the original measurement for possible errors), we may derive information supporting multiple possibilities. For example, if the actual maximum measured height at a location was 30 feet, and the error interval was plus-or-minus 30 feet (which might be derived from known inaccuracies in the DTM or in the estimation of the altitude of possible observers), we have evidence supporting the possibility of the true maximum height falling into any of the three categories MINIMUM HEIGHT, NAP-OF-THE-EARTH, or CONTOUR.[2] This information may be easily converted into a belief function over the INTERVISIBILITY frame.

In a similar fashion, topographic data and vegetation overlays are converted to belief functions. Examples are shown in Figures 3 and 4.

In the remainder of this paper, we review evidential reasoning, using examples from the local-area-characteriztion problem to illustrate key points. An analysis of the potential risk associated with operations in an area based on the knowledge structures created is carried out using typical input bodies of evidence.

2 Evidential Reasoning

For the past several years (see [Low82,GLF81,LG83b,LG83a,LSG86,Wes86]), we have been addressing perceptual problems that bridge the gap between low-level sensing and high-level reasoning. Problems that fall into this gap are often characterized by multiple evidential sources of real-time data, which must be properly integrated with general knowledge about the world to provide an understanding of the situation that is sufficiently rich to support high-level goals. In this section, we briefly describe a formal framework for reasoning with perceptual data that forms the basis for evidential reasoning[3] systems.

2.1 Background

The information required to understand the current state of the world comes from multiple sources: real-time sensor data, previously stored general knowledge, and current contex-

[2] In practise, accounting for possible errors will be handled directly by the evidential reasoning *discounting* operation.

[3] *Evidential reasoning* is a term coined by SRI International [LG82] to denote the body of techniques specifically designed for manipulating and reasoning from evidential information as characterized in this paper.

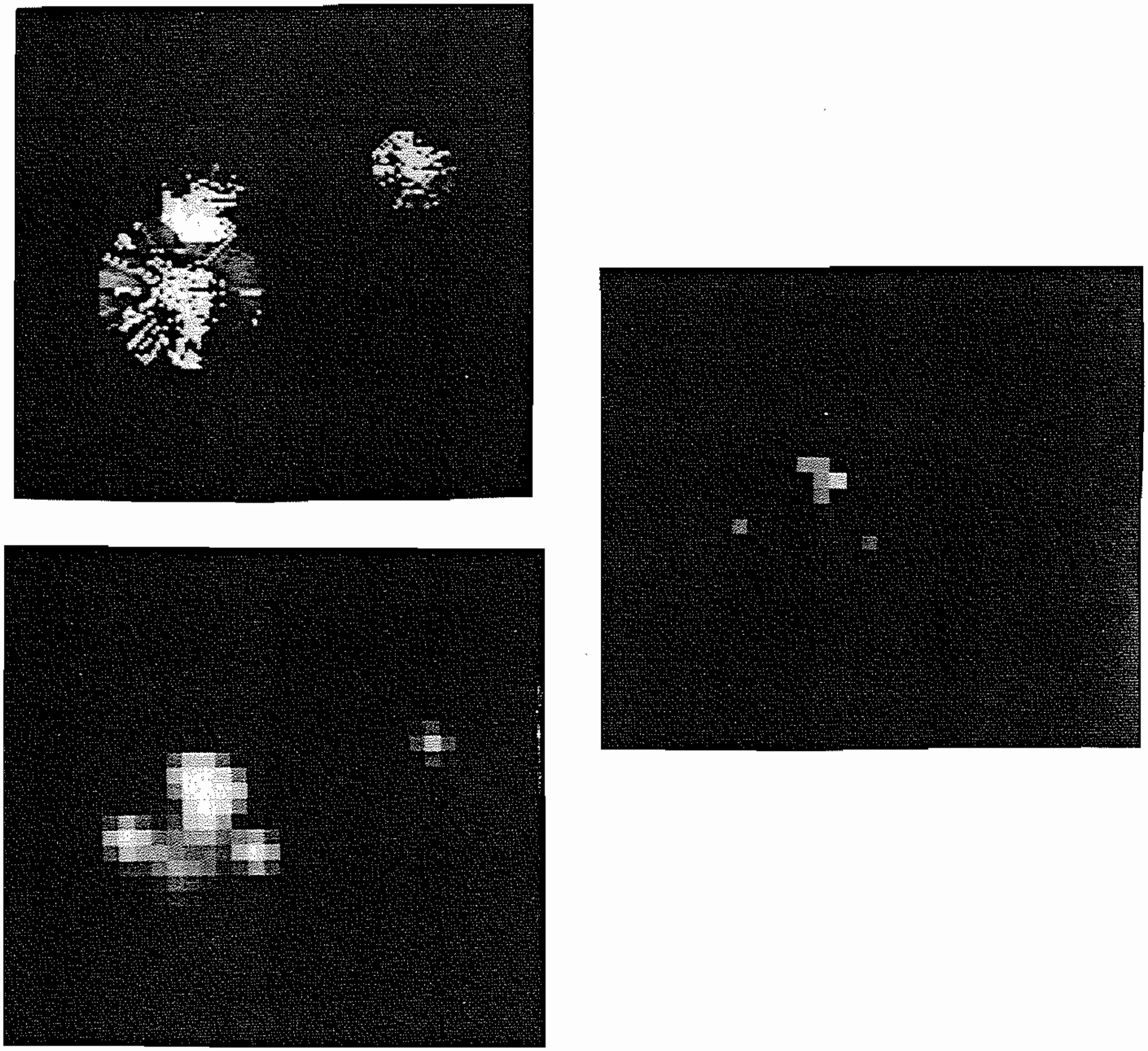

Figure 2: Intervisibility Maps. (a) Original Level-7 intervisibility map (darker areas have higher safe altitudes); (b) sampled intervisibility map; (c) INTERVISIBILITY belief function.

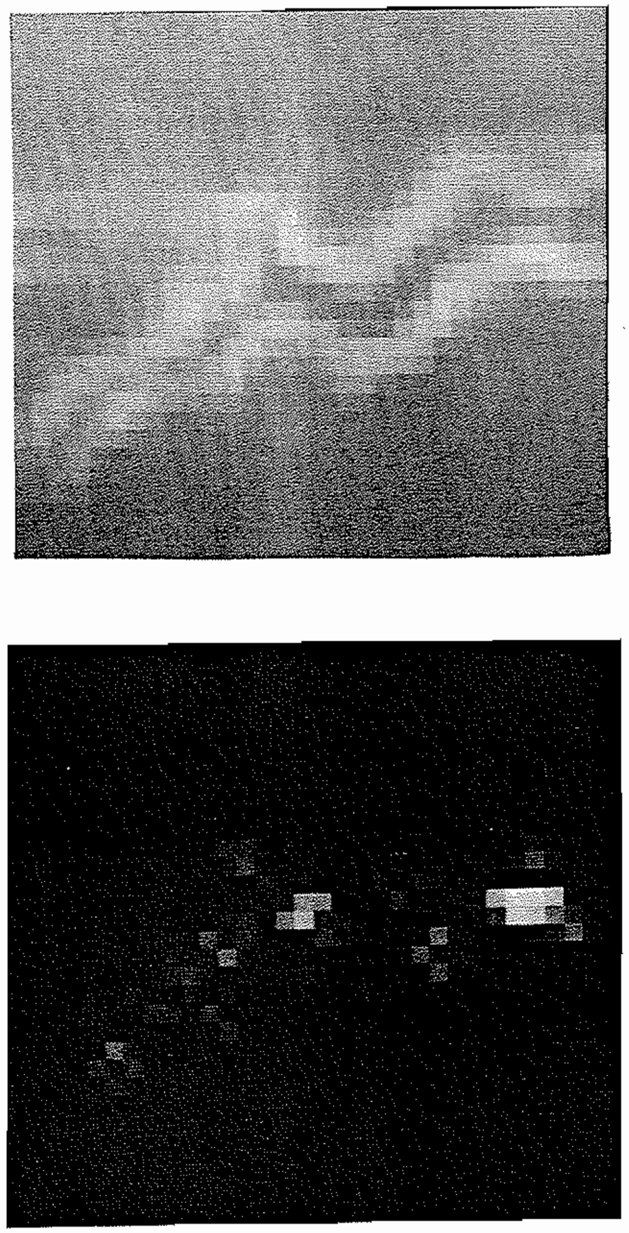

Figure 3: Topography data. (a) Sampled totpography data (rough areas, computed from height variance, are shown as dark regions). (b) TOPOGRAPHY belief function.

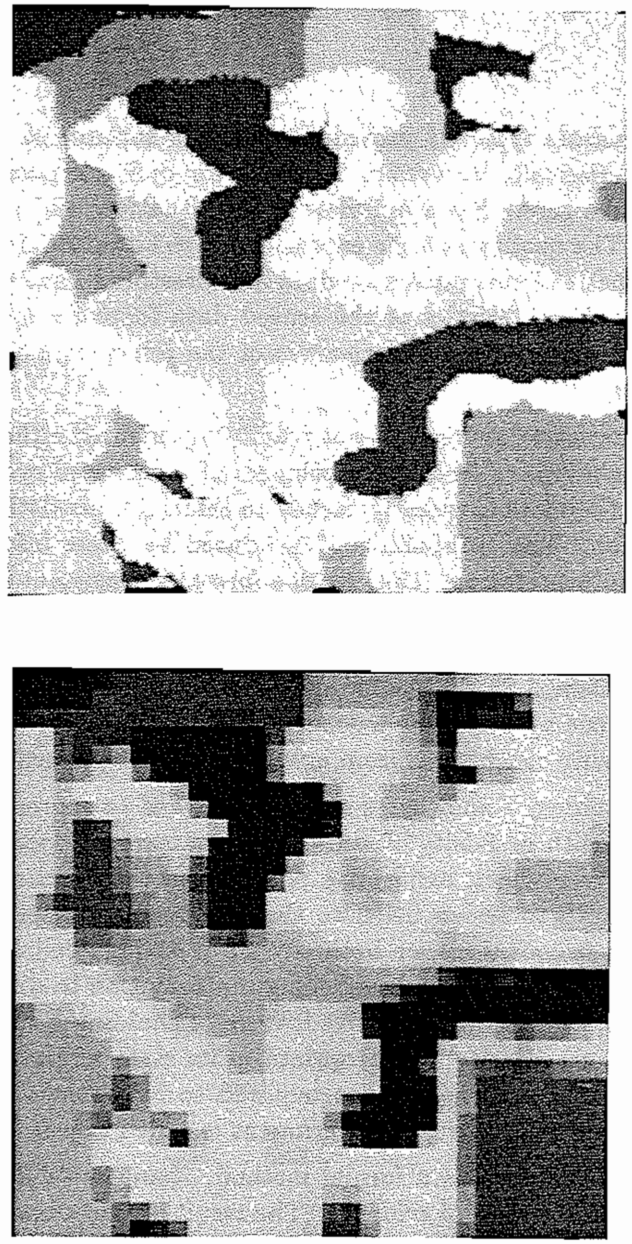

Figure 4: Vegetation data. (a) Original overlay (dense vegetation is shown as dark areas). (b) Resulting belief function.

tual information. Sensors typically provide *evidence* in support of certain interpretations. Evidence is characteristically uncertain: It allows for multiple possible explanations; it is incomplete: the source rarely has a full view of the situation; and it may be completely or partially incorrect. The quality and the ease with which situational information may be extracted from a synthesis of current sensor data and prestored knowledge is a function both of how strongly the characteristics of the sensed data focus on appropriate intermediate conclusions and the strength and effectiveness of the relations between those conclusions and situation events.

Given its characteristics, evidence is not readily represented either by logical formalisms or by classical probabilistic estimates. Developers of automated systems that must reason from evidence have therefore frequently turned to informal, heuristic methods for handling uncertain information. The "probabilities" produced by these informal approaches often cause difficulties in interpretation. The lack of a formally consistent method can cause problems in extending the capabilities of such systems effectively. Our work in evidential reasoning was motivated by these shortcomings. Our theory is based on the Shafer-Dempster theory of evidence [Dem68,Sha76,Sha86] and aims to overcome some of the difficulties in reasoning from evidence by providing a natural representation for evidential information, a formal basis for drawing conclusions from evidence, and a representation for belief.

In evidential reasoning, a knowledge source is allowed to express probabalistic opinions about the (partial) truth or falsity of statements that are composed of subsets of propositions from a space of distinct, exhaustive possibilities (called the *frame of discernment*). The theory allows a KS to assign belief to the individual propositions in the space or to disjunctions of these propositions, or both. When it assigns belief to a disjunction, a KS is explicitly stating that it does not have enough information to distribute this belief more precisely. This condition has the attractive feature of enabling a KS to distribute its belief to statements whose granularity is appropriate to its state of knowledge. Also, the statements to which belief is assigned are not required to be distinct from one another. The distribution of beliefs over a frame of discernment is called a *body of evidence.*

Evidential reasoning provides a formal method, *Dempster's Rule of Combination*, for fusing (i.e., pooling) two bodies of evidence. The result is a new body of evidence representing the consensus of the two original bodies of evidence, which may in turn be combined with other evidence. Because belief may be associated directly with a disjunction of propositions, the probability in any selected proposition is typically underconstrained. This necessitates an interval measure of belief, because belief associated with a disjunction may, based upon additional information, devolve entirely upon any one of the disjuncts. Thus, an interval associated with a proposition implies that the true probability associated with that proposition must fall somewhere in the interval. A side-effect of applying Dempster's rule is a measure of *conflict* between the two bodies of evidence that provides a means for detecting possible gross errors in the information.

Current expert-systems technology is most effective when domain knowledge can be modeled as a set of loosely interconnected concepts (i.e., propositions) [DK77]; this loose interconnection justifies an *incremental* approach to updating beliefs. In most of our work, there is the potential for strong interconnectivity among beliefs in propositions. We therefore focus on a body of evidence as a primitive, meaningful collection of interrelated (dependent) beliefs; updating the belief in one proposition affects the entire body of evidence. Other work has addressed the concept of a body of evidence in a production-rule formalism [Kon79,LB82] by creating special entities.

Evidential reasoning provides options for the representation of information: independent opinions are expressed by multiple (independent) bodies of evidence; dependent opinions (in which belief in one proposition depends on that of another) can either be expressed by a single body of evidence or by a network that describes the interrelationships among several bodies of evidence. These networks of bodies of evidence capture the geneology of each body (similar in spirit to [Coh85]) and are used in a manner similar to data-flow models [WA84], updating interrelated beliefs (i.e., for belief revision [Doy81]).

In this section we assume some familiarity with the Dempster-Shafer theory of beliefs, although the appropriate equations from this theory are included. We begin with a discussion of the formal approach to the problem of reasoning from evidence and then progress to a description of the implementation approach, including an example. We close with a short description of the system that we have developed for applying evidential reasoning.

2.2 The Formal Approach

2.2.1 Framing the Problem

The first step in applying evidential reasoning to a given problem is to delimit a propositional space of possible situations. Within the theory of belief functions, this propositional space is called the *frame of discernment*. It is so named because all bodies of evidence are expressed relative to this surrounding framework, and it is through this framework that the interaction of the evidence is discerned. A frame of discernment delimits a set of possible situations, exactly one of which is true at any one time. For example, our problem is to characterize locations for helicopter operations, and ultimately relate these characterizations to a "quality-of-life" measure for helicopters at each location. One possible characterization would be based on the topography at the particular location. In this case, the frame of discernment consists of the set of all possible types of topography. This frame might be represented by a small set Θ_A, in which each element a_i corresponds to a possible type (e.g., DENSE-FOREST, SPARSE-FOREST, SCRUB, and CLEAR):

$$\Theta_A = \{a_1, a_2, \ldots, a_n\} \quad .$$

Once a frame of discernment has been established, propositional statements can be represented by disjunctions of elements from the frame corresponding to those situations for which the statements are true. For example, the proposition A_i might correspond to the statement "the area is forested," in which case A_i would be represented by the subset of elements from Θ_A that correspond to specific types of forest (e.g., DENSE-FOREST and SPARSE-FOREST):

$$\mathsf{A}_i \subseteq \Theta_A \quad .$$

Other propositions describing the topography for this area can be similarly represented as subsets of Θ_A (i.e., as elements of the power set of Θ_A, denoted 2^{Θ_A}). Once this has been accomplished, logical questions can be posed and resolved in terms of the frame; logical operations and relations can be resolved through set operations and relations.

Additional interesting aspects of map areas may be similarly represented by additional frames of discernment. For example, the vegetative cover (to permit the helicopter to become *masked*) in an area of the map may be defined by the frame Θ_B, which could include elements corresponding to the types of vegetation that may be present in that area. Propositional statements pertaining to vegetation can then be defined relative to this frame; i.e.,

$$\begin{aligned} \Theta_B &= \{b_1, b_2, \ldots, b_n\} \\ \mathsf{B}_j &\subseteq \Theta_B \quad . \end{aligned}$$

So far, propositional statements pertaining to topography or vegetation in an area can be addressed separately, but they cannot be jointly considered. To do this, one must first define a *compatibility relation* between the two frames. A compatibility relation simply describes which elements from the two frames can be true simultaneously. Thus, the compatibility relation between frames Θ_A and Θ_B is a subset of the cross product of the two frames. A pair (a_i, b_j) is included if and only if they can be true simultaneously. There is at least one pair (a_i, b_j) included for each a_i in Θ_A (the analogue is true for each b_j):

$$\Theta_{A,B} \subseteq \Theta_A \times \Theta_B \quad .$$

Using the compatibility relation $\Theta_{A,B}$, we can define a *compatibility mapping* $C_{A \mapsto B}$ for translating propositional statements expressed relative to Θ_A to statements relative to Θ_B. If a statement A_k is true, then the statement $C_{A \mapsto B}(\mathsf{A}_k)$ is also true:

$$\begin{aligned} C_{A \mapsto B} : 2^{\Theta_A} &\mapsto 2^{\Theta_B} \\ C_{A \mapsto B}(\mathsf{A}_k) &= \{b_j | (a_i, b_j) \in \Theta_{A,B}, a_i \in \mathsf{A}_k\} \quad . \end{aligned}$$

Instead of translating propositional statements between these two frames via $C_{A \mapsto B}$ and $C_{B \mapsto A}$, we might choose to translate these statements to a common frame that captures all of the information. This common frame is identical to the compatibility relation $\Theta_{A,B}$. Frame Θ_A (and analogously Θ_B) is then simply related to frame $\Theta_{A,B}$[LSG86].

Clearly, as more aspects of geographic areas become of interest, the number and complexity of the frames and compatibility mappings increase. However, there is a trade-off between the complexity of individual frames and the complexity of the network of compatibility mappings connecting them. We might define a single (complex) frame that encompasses all aspects of interest or, alternatively, define a (complex) network of frames (called a *gallery*) that includes a distinct frame for each aspect of interest. These may not be equivalent.

2.2.2 Analyzing the Evidence

Once a gallery has been established, the available evidence can be analyzed and interpreted. The goal of this analysis is to establish a line of reasoning, based upon both the possibilistic information in the gallery and the probabilistic information from the evidence, that determines the most likely answers to some questions. The gallery delimits the space of possible situations, and the evidential information establishes the likelihoods of these possibilities. Within an analysis, bodies of evidence are expressed relative to frames in the gallery, and paths are established for the bodies of evidence to move through the frames by means of the compatibility mappings. An analysis also specifies other evidential operations to be performed, including whether multiple bodies of evidence are to be combined (*fused*) when they arrive at common frames. Finally, an analysis specifies which frame and ultimate bodies of evidence are to be used to answer each target question. Thus, an analysis specifies a means of arguing from multiple bodies of evidence toward a particular (probabilistic) conclusion. An analysis, in an evidential context, is the analogue of a proof tree in a logical context.

To begin, each body of evidence is expressed relative to a frame in the gallery. Each is represented as a mass distribution (e.g., m_A) over propositional statements discerned by a frame (e.g., Θ_A):

$$\begin{aligned} m_A : 2^{\Theta_A} &\mapsto [0,1] \\ \sum_{\mathsf{A}_i \subseteq \Theta_A} m_A(\mathsf{A}_i) &= 1 \\ m_A(\emptyset) &= 0 \ . \end{aligned}$$

Intuitively, mass is attributed to the most precise propositions a body of evidence supports. If a portion of mass is attributed to a proposition A_i, it represents a minimal commitment to that proposition and all the propositions it implies. Additional mass attributed to a proposition A_j that is compatible with A_i, but does not imply it (i.e., $\emptyset \neq \mathsf{A}_i \cap \mathsf{A}_j \neq \mathsf{A}_j$), represents a potential commitment: mass that neither supports nor denies that proposition at present but might later move either way based upon additional information.

To *interpret* this body of evidence relative to the question A_j, we calculate its *support* and *plausibility* to derive its *evidential interval* as follows:

$$\begin{aligned} Spt(\mathsf{A}_j) &= \sum_{\mathsf{A}_i \subseteq \mathsf{A}_j} m_A(\mathsf{A}_i) \\ Pls(\mathsf{A}_j) &= 1 - Spt(\Theta_A - \mathsf{A}_j) \\ [Spt(\mathsf{A}_j), Pls(\mathsf{A}_j)] &\subseteq [0,1] \ . \end{aligned}$$

The lower bound of an evidential interval indicates the degree to which the evidence supports the proposition, while the upper bound indicates the degree to which the evidence fails to refute the proposition, i.e., the degree to which it remains plausible. This evidential interval, for the most part, corresponds to bounds on the probability of A_j. Thus, complete ignorance is represented by an evidential interval of $[0.0, 1.0]$ and a precise probability assignment is represented by the "interval" collapsed about that point (e.g., $[0.7, 0.7]$). Other degrees of ignorance are captured by evidential intervals with widths other than 0 or 1 (e.g., $[0.6, 0.8], [0.0, 0.5], [0.9, 1.0]$).

If a body of evidence is to be interpreted relative to a question expressed over a different frame from the one over which the evidence is expressed, a path of compatibility relations connecting the two frames is required. The mass distribution expressing the body of evidence is then repeatedly *translated* from frame to frame, by means of compatibility mappings, until it reaches the ultimate frame of the question. In translating m_A from frame Θ_A to frame Θ_B by means of compatibility mapping $C_{A \mapsto B}$, the following computation is applied to derive the translated mass distribution m_B:

$$m_B(B_j) = \sum_{C_{A \mapsto B}(A_i) = B_j} m_A(A_i) \quad .$$

Intuitively, if we (partially) believe A_i, and A_i implies B_j, then we should have the same (partial) belief in B_j. This same method is applied to move mass distributions among frames that represent states of the world at different times. However, when this is the case, the operation is called *projection*.

Once two mass distributions m_A^1 and m_A^2 representing independent opinions are expressed relative to the same frame of discernment, they can be fused (i.e., combined) using *Dempster's Rule of Combination*. Dempster's rule pools mass distributions to produce a new mass distribution m_A^3 that represents the consensus of the original disparate opinions. That is, Dempster's rule produces a new mass distribution that leans towards points of agreement between the original opinions and away from points of disagreement. Dempster's rule is defined as follows:

$$\begin{aligned} m_A^3(A_k) &= (1-k)^{-1} \sum_{A_i \cap A_j = A_k} m_A^1(A_i) m_A^2(A_j) \\ k &= \sum_{A_i \cap A_j = \emptyset} m_A^1(A_i) m_A^2(A_j) \neq 1 \quad . \end{aligned}$$

Because Dempster's rule is both commutative and associative, multiple (independent) bodies of evidence can be combined in any order without affecting the result. If the initial bodies of evidence are independent, then the derivative bodies of evidence are independent, if they share no common ancestors. Thus, in the course of constructing an analysis, we must ensure that evidence is propagated and combined in such a way to guarantee the independence of the evidence at each combination.

Other evidential operations include *discounting*, *summarization*, and *gisting* (among others). Discounting adjusts a mass distribution to reflect its source's credibility (expressed as a discount rate $r \in [0, 1]$). Summarization eliminates extraneous details from a mass distribution by collecting all of the extremely small amounts of mass attributed to propositions and attributing the sum to the disjunction of those propositions. Gisting produces the "central" Boolean-valued statement that captures the essence of a mass distribution. This is particularly useful when explaining lines of reasoning.

3 Characterizing Geographic Areas

In implementing this formal approach, we have found that the gallery, frames, compatibility relations, and analyses can all be represented straightforwardly as graphs consisting of nodes connected by directed edges, and therefore we use Grasper II [Low86,Low78], a programming language extension to LISP that introduces graphs as a primitive data type. A graph in Grasper II consists of a set of labeled subgraphs. Each subgraph consists of a set of labeled nodes and a set of labeled, directed edges that connect pairs of nodes. Each node, edge, and subgraph has a value that can be used as a general repository for information. Once the graphical representations have been established for the gallery, frames, compatibility relations, and analyses, the remainder of the formal approach is easily implemented.

The first step is to define the gallery (Figure 5). In this case, we have selected VEGETATION, TOPOGRAPHY, and INTERVISIBILITY as the three frames that will represent the primitive characterizations of a geographical area. VEGETATION and TOPOGRAPHY are combined into a joint frame, which is in turn linked to a frame, EXPOSURE, that attempts to capture the degree to which a helicopter may be exposed based on vegetation and terrain types.[4] INTERVISIBILITY measures the maximum altitude at which the aircraft can fly without risking direct observation by a location known to contain hostile forces; the higher this altitude, the less chance the helicopter has of being observed at normal tactical altitudes. INTERVISIBILITY and EXPOSURE are combined, and this combined frame is then related to an overall measure of RISK for the helicopter.

The next step is to define the frames in the gallery. Each of these is represented by a subgraph sharing the same name as a node from the gallery. Each such subgraph includes a node for each element of the frame and may include additional nodes representing aliases, i.e., named disjunctions of elements. Each of these additional nodes have edges pointing to elements of the frame (or other aliases) that make up the disjunction. The VEGETATION frame (Figure 6) has four nodes representing vegetation types, as well as two aliases (FOREST and VEGETATED). The TOPOGRAPHY frame (Figure 7) has four nodes representing possible terrain types, plus one alias.

Each compatibility relation in the gallery is represented as a subgraph that includes the nodes from the two interrelated frames with edges connecting the compatible elements. For example, Figure 8 shows a portion of the INTERVISIBILITY&EXPOSURE-RISK compatibility relation. Among other things, this relation indicates that ABOVE-LOW-LEVEL&HIGH is compatible with either VERY-LOW-RISK or LOW-RISK.

After the gallery and its supporting frames and compatibility relations have been established, evidential analyses can be constructed. These analyses are represented as data-flow

[4]This frame attempts to capture the notion that in certain types of terrain, the helicopter is able to become masked more easily than in others.

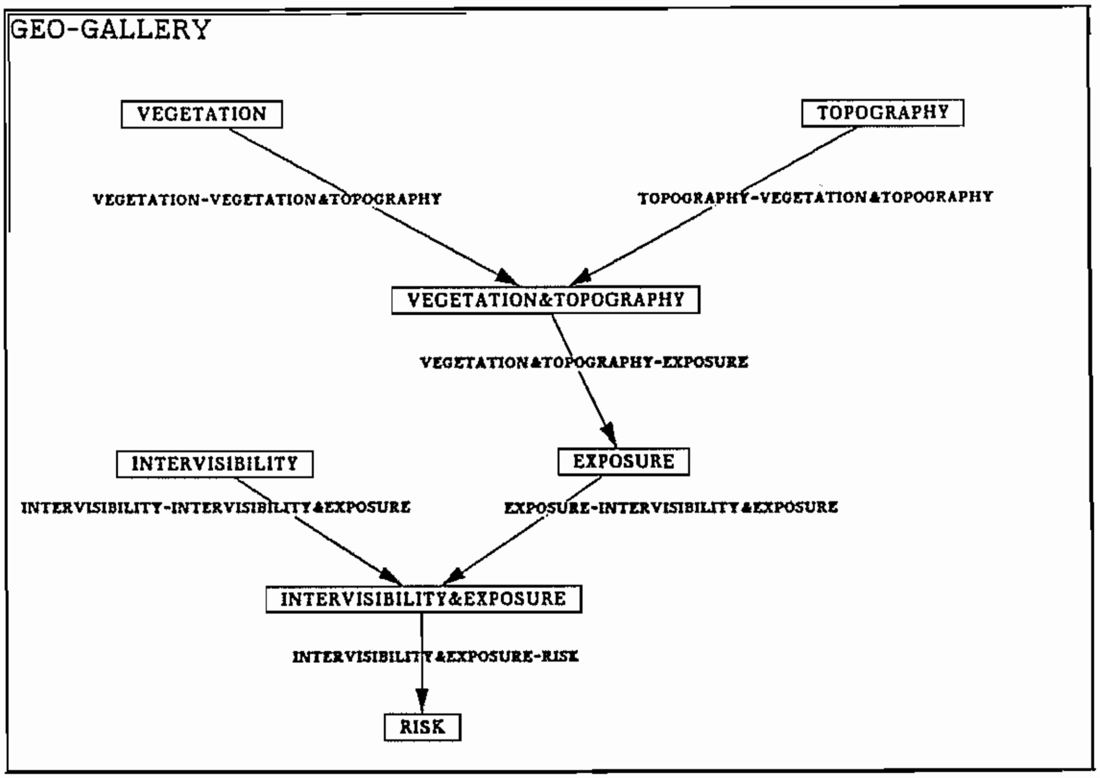

Figure 5: The GEO-GALLERY Gallery.

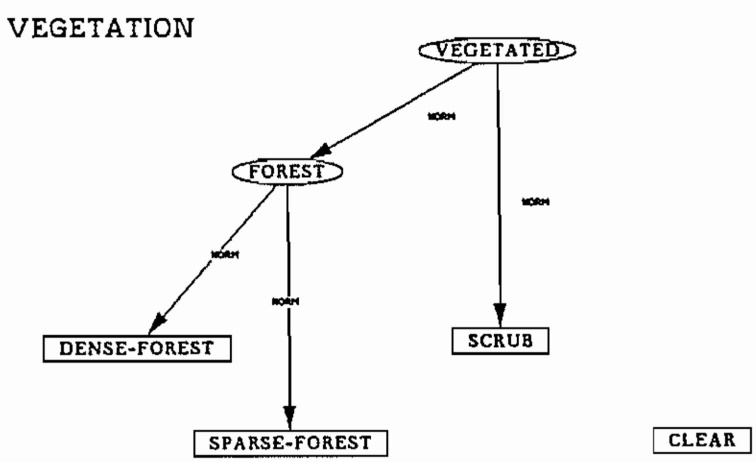

Figure 6: VEGETATION Frame.

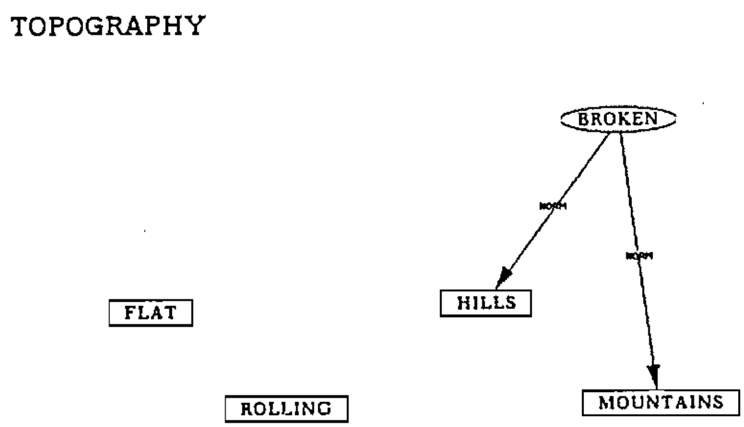

Figure 7: TOPOGRAPHY Frame.

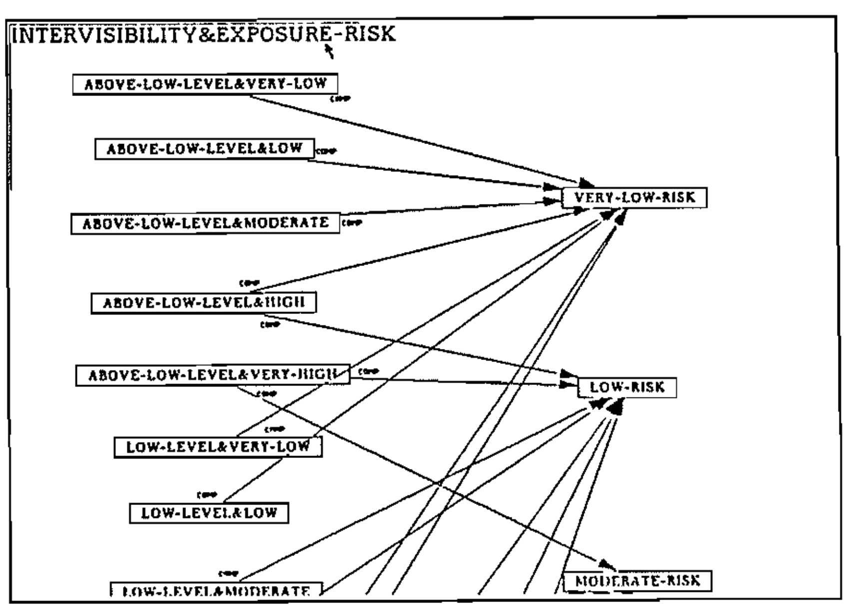

Figure 8: A portion of the INTERVISIBILITY&EXPOSURE-RISK Compatibility Relation.

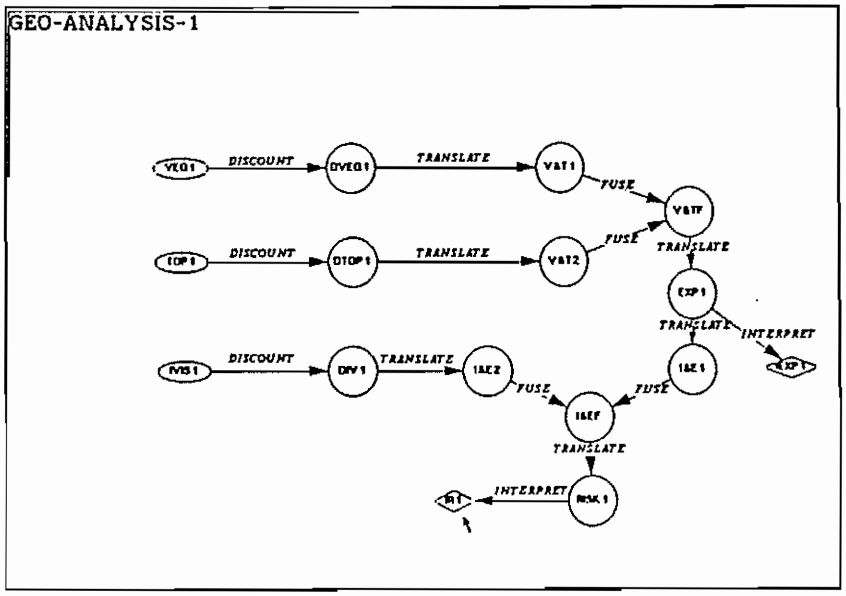

Figure 9: GEO-ANALYSIS1 Analysis.

graphs where the data and the operations are evidential. Figure 9 is one such analysis. Here primitive bodies of evidence are shown as elliptical nodes, derivative bodies of evidence are represented by circular nodes, and diamond-shaped nodes represent interpretations of bodies of evidence. The values of these nodes contain the information (i.e., data) that they represent (Figure 10). For bodies of evidence this information includes a frame of discernment, a mass distribution, and other supporting information. Edges pointing to a derivative node are labeled with the evidential operation that generates the body of evidence represented by this node.

In the analysis to be performed for each geographic area, there are three primitive bodies of evidence. These correspond to topographic information derived from a digital terrain map, vegetation information provided by factor-overlays, and intervisibility information provided by a pre-computed intervisibility map. The bodies of evidence derived from these are shown in Figure 9.[5] VEG1 indicates that the area is FOREST, which results in a mass-function that distributes the entire unit of belief over the disjunction, DENSE-FOREST or SPARSE-FOREST. TOP1 states there is a 60 percent chance that the terrain type is MOUNTAINS, a 20 percent chance that it is HILLS, and 20 percent that it is either one. IVIS1 allocates 30 percent of its evidential mass to a maximum visible height of ABOVE-

[5] In these examples, the mass functions are the primary items of interest. They are indicated by MASS-FUN: in the windows, and they are represented by a list of the form: (((prop11 prop12 ...) mass1)((prop21 prop22 ...) mass2) ...((propn1 propn2 ...) massn)).

```
VEG1
TYPE: PRIMITIVE
FOD: (VEGETATION 1.)
USER-MASSFUN: (((FOREST) 1.0))
MASSFUN: (((DENSE-FOREST SPARSE-FOREST) 1.0))
Exit
```

```
TOP1
TYPE: PRIMITIVE
FOD: (TOPOGRAPHY 1.)
USER-MASSFUN: (((HILLS MOUNTAINS) 0.2) ((HILLS) 0.2) ((MOUNTAINS) 0.6))
MASSFUN: (((MOUNTAINS) 0.6) ((HILLS MOUNTAINS) 0.2) ((HILLS) 0.2))
Exit
```

```
IVIS1
TYPE: PRIMITIVE
FOD: (INTERVISIBILITY 1.)
USER-MASSFUN: (((ABOVE-LOW-LEVEL) 0.3) ((ABOVE-LOW-LEVEL LOW-LEVEL) 0.2) ((CONTOUR) 0.3) ((LOW-LEVEL) 0.2))
MASSFUN: (((ABOVE-LOW-LEVEL) 0.3) ((CONTOUR) 0.3) ((ABOVE-LOW-LEVEL LOW-LEVEL) 0.2) ((LOW-LEVEL) 0.2))
Exit
```

```
DVEG1
TYPE: DISCOUNT
DISCOUNT-RATE: 10.
FOD: (VEGETATION 1.)
MASSFUN: (((DENSE-FOREST SPARSE-FOREST) 0.9) ((DENSE-FOREST CLEAR SPARSE-FOREST SCRUB) 0.1))
Exit
```

```
IEXP1
TYPE: INTERPRETATION
PROPOSITIONS: (VERY-LOW LOW MODERATE (HIGH VERY-HIGH))
FOD: (EXPOSURE 1.)
CONCLUSIONS: (((VERY-LOW) (0.48600006 1.0)) ((LOW) (0.0 0.51399994)) ((MODERATE) (0.0 0.18999994)) ((HIGH VERY-HIGH) (0.0 0.18999994)))
Exit
```

```
RISK1
(((VERY-LOW-RISK) 0.73636365) ((VERY-LOW-RISK MODERATE-RISK LOW-RISK) 0.114545465) ((HIGH-RISK MODERATE-RISK LOW-RISK VERY-LOW-RISK) 0.0
01818186) ((LOW-RISK VERY-LOW-RISK) 0.04909092) ((LOW-RISK VERY-LOW-RISK HIGH-RISK MODERATE-RISK VERY-HIGH-RISK) 0.01818182))

Exit
```

```
IF1
TYPE: INTERPRETATION
PROPOSITIONS: (SAFE HAZARDOUS DANGEROUS)
FOD: (RISK 1.)
CONCLUSIONS: (((SAFE) (0.7854546 1.0)) ((HAZARDOUS) (0.0 0.21454543)) ((DANGEROUS) (0.0 0.099999964)))
Exit
```

Figure 10: Data from GEO-ANALYSIS1.

LOW-LEVEL, 30 percent to CONTOUR, 20 percent to either ABOVE-LOW-LEVEL or LOW-LEVEL, and 20 percent to LOW-LEVEL alone.

Each of these bodies of evidence is discounted, reflecting a certain amount of doubt in the credibility of these measurements. For example, DVEG1 in Figure 10 shows how the initial specification of FOREST for the vegetation has been discounted to allow for a small amount of mass (10 percent of the total) to be distributed to alternative possibilities. Following Figure 9, the discounted bodies of evidence, DVEG1 and DTOP1 are each translated into the VEGETATION&TOPOGRAPHY frame, and then fused; the result of this fusion operation (the body of evidence shown as V&TF in Figure 9) is then translated first into the EXPOSURE frame (EXP1) and then into the INTERVISIBILITY&EXPOSURE frame (I&E1).[6] We have an interpretation node, IEXP1, depending from evidential node EXP1, which shows that the first two bodies of evidence combine to provide significant evidence for VERY-LOW exposure. Interpretation nodes of this sort enable us to track intermediate results for propositions of interest.b After discounting IVIS1 and similarly translating the result into the INTERVISIBILITY&EXPOSURE (I&E2), the new body of evidence is fused with I&E1, and translated directly to the RISK frame (evidential node RISK1 in Figure 10).

In order to better understand the impact of this analysis in terms of interest to the helicopter mission-planner, the results are *interpreted*. The node, IR1, provides an interpretation in terms of the RISK aliases, SAFE, HAZARDOUS, and DANGEROUS, showing intervals of (approximately) $[.79, 1.0]$, $[0.0, .21]$, and $[0.0, 0.1]$, respectively – the analysis indicates this is likely to be a safe region. Figure 11 shows the result of performing this analysis on each of the local areas of the original map.

Once such a prototypical analysis is developed, refined, and tested, the resulting data-flow structures may be directly reduced to a Lisp procedure which may then be applied to bodies of evidence previously constructed over the area of interest. Upon review of the resulting primitive assessments, and the results of clustering operations, the user may decide to modify this analysis structure, and reclassify. This is quite straightforward, given the capability and flexibility of the Gister system.

4 Evidential-Reasoning Systems

Gister was originally developed to support the construction, modification, and interrogation of evidential analyses, such as those described here. Gister provides an interactive, menu-driven, graphical interface that allows these structures to be easily manipulated. The user simply selects from a menu to add an evidential operation to an analysis, to modify operation parameters (e.g., discount rates), or to change any portion of a gallery, including its frames and compatibility relations. In response, Gister updates the analyses.

All of the figures in this paper are actual screen images from Gister. Figure 9 includes the menus for working with analyses. On the left side of the screen is a menu of nouns. The

[6] These cascaded compatibility relations could have been combined into a single composite relation and corresponding translation.

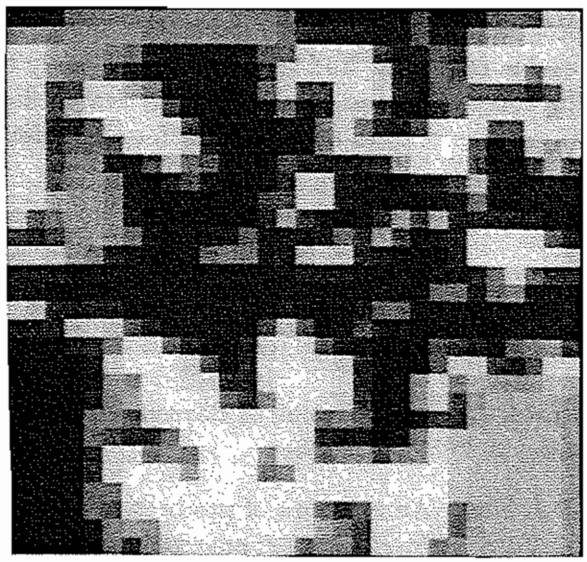

Figure 11: The RISK belief function resulting from an analysis of each local area (dark areas indicate VERY-LOW-RISK).

user determines with what class of objects he wishes to work and selects the appropriate noun from the menu. Once a noun has been selected, a menu of verbs appears on the right side of the screen. A selection from this menu invokes the operation corresponding to the selected verb on the previously selected noun. The user then designates the appropriate nodes, edges, and the like for the selected operation.

5 Summary

Evidential reasoning has already been successfully applied to problems in several domains, including multisensor integration for situation assessment and Naval Intelligence analysis. The addition of the compatability relation to the theory of beliefs, the formalization and development of new evidential operators, and the use of graphical representations have greatly improved the overall usefulness and accessibility of these techniques. Further developments carried out under this program of research have led to the ability to compile analysis networks into directly executable Lisp code, and to the ability to apply these directly to images and image-like data. This approach seems to offer a great deal of flexibility in interactively specifying appropriate knowledge sources and their use for characterizing geographic areas.

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