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Using
Expert Systems in
Mine Warfare

by

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Historically, sea mines warfare have played an important role in warfare, which a naval officer cannot afford to neglect. During the recent mine campaign in the Middle East involving Iran an Iraq, commanders delayed decisions on whether or not to deploy mine countermeasure (MCM) forces. As a result, damage occurred to ships in a minefield that could have been prevented by the speedy application of MCM. Before the operational mission commenced, there are several uncertain questions in the mind of the commander: Do the mine-fields exist? Which country laid the mines? What type of delivery platform laid the mines? Where are the mines? What kind of mines are they? Do we need to deploy the MCM forces? Previously, these kinds of fuzzy questions were very difficult to answer by a tactical principle.

In this thesis, the probabilistic inference network in the expert system environment is used to answer the above questions. The probabilistic inference network method is supported by the certainty factors. Calculations involving quantitative probabilities for answers to the above questions could enable the MCM experts to offer suggestions to the commander for reducing the ship's vulnerability at sea during wartime.

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Using

Expert Systems in

Mine Warfare

by

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ABSTRACT

Historically, sea mines warfare have played an important role in warfare, which a naval officer cannot afford to neglect. During the recent mine campaign in the Middle East involving Iran and Iraq, commanders delayed decisions on whether or not to deploy mine countermeasure (MCM) forces. As a result, damage occurred to ships in a minefield that could have been prevented by the speedy application of MCM. Before an operational mission is commenced, there are several uncertain questions in the mind of the commander: Do the mine-fields exist? Which country laid the mines? What type of delivery platform laid the mines? Where are the mines? What kind of mines are they? Do we need to deploy the MCM forces? Previously, these kinds of fuzzy questions were very difficult to answer by a tactical principle.

In this thesis, the probabilistic inference network in an expert system environment is used to answer the above questions. The probabilistic inference network method is supported by the certainty factors. Calculations involving quantitative probabilities for answers to the above questions could enable the MCM experts to offer suggestions to the commander for reducing the ship's vulnerability at sea during wartime.

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I. INTRODUCTION

The goal of this thesis is to design a probabilistic inference network as an expert system for use in mine warfare. This inference network can be used to offer suggestions to the commander for reducing the ship's vulnerability at sea. This chapter discusses the problems of mine warfare and the objectives of the thesis.

A. THE PROBLEM STATEMENT

Mines are increasingly becoming a weapon of choice. They are a powerful political, as well as, military option. Stress and uncertainty lie at the heart of mine warfare. Minefields are similar to the twilight zone—they work more on human minds than on the ships themselves. As we can see from the mine chronology [Ref. 1:p. 291-295], mine warfare has been a part of history since the beginning of 600 B.C. There are many questions faced by the commanders involving the prediction of events: Will there be a minefield? Which country will be involved? What delivery platform will lay the mines? Where will be the minefields? What kind of mines will there be? Dependent on the answer to these questions the commander will consider the deployment of mine countermeasure (MCM) forces. The specific reasons for any decision are often obscure, and the decision to avoid a minefield or to risk it is influenced by many factors; one of them is the decision maker's perception of the minefield.

In many practical problem-solving situations, the available knowledge is incomplete or inexact. Weather prediction and medical diagnosis are two examples. In cases such as these, our knowledge is not adequate enough to use precise logic inference. However, people have ways of drawing inferences from incomplete, inexact, or uncertain knowledge and information. Although our knowledge is not complete, we can and do make generalizations and approximations that help us summarize our experiences and predict the outcome of events. Generalizations are often subject to error, and yet we still use them because they provide a useful probabilistic tool.

The knowledge in a machine is also limited. Intelligent machines often work with incomplete information in the form of quantitative approximations. Probabilistic reasoning methods allow fuzzy logic (FL) to use uncertain or probabilistic knowledge to derive a confident decision. In addition, probabilistic methods can help us accumulate evidence for hypotheses in a fair way; they are appropriate tools in making "just" decisions. Decision theory, related to the theory of probability, provides additional techniques that help to minimize risk in making decisions. Therefore, it is appropriate to use the probabilistic reasoning methods in expert systems to solve the decision problems involved in mine warfare. The decision factors are represented by levels in the probabilistic inference networks. Calculations involving quantitative probabilities for answers to the questions in building an inference network could offer suggestions to the commander for reducing the ship's vulnerability at sea during wartime.

B. THESIS OBJECTIVES

The Naval mine is defined as follows [Ref. 2:p. 2-1]:

> **A mine is an explosive device laid in the water with the intention of damaging or sinking ships or of deterring shipping from entering an area. The term does not include devices attached to the**

bottoms of ships or to harbor installations by personnel operating underwater, nor does it include devices that explode immediately on expiration of a predetermined time after laying.

They are two main purposes that may be served by mine warfare:

- **To damage** or destroy enemy shipping.

- **To deny the enemy** use of certain waters, or at least hinder his operations in these waters by the threat presented by a minefield.

For a minefield to accomplish the first purpose, it must be laid in secret in a busy shipping lane. Secrecy is essential, for if the enemy suspects a minefield is present, he can sweep to eliminate the mines or perhaps simply reroute shipping around the field. The requirement that the field be laid in secret usually restricts the number of mines that can be used. Therefore, a large number of ships must pass through the field before the probability of a hit becomes great enough to be significant.

Minefields laid to accomplish the second purpose should be highly advertised after planting in order to deter enemy shipping. Knowing of the presence of the mines, the enemy will attempt to render the field harmless by sweeping operations. Consequently, some effort must be devoted to keeping the field active. This means that the field must be reseeded at a rate equivalent to the sweeping rate of the enemy.

Mine warfare is complex, obscure, and controversial. Yet it is an important adjunct of the capacity of countries to wage war. Mines have been used in wars for many centuries and history shows that mine warfare is a constant struggle between the mine designer and MCM. Mine warfare is therefore a battle of wits between the mine user and his enemy's countermeasures. In this thesis, concentration is on the MCM, within a specific operational mission, to clear up mines that were laid by the defensive country in the approaching sea area. It is very difficult, without sufficient information about minefields, for the commander of mine warfare to make a decision whether to deploy MCM forces. Therefore, we seek to model general decision-making in a computationally practical, yet mathematically meaningful way. Here the "probabilistic inference network" structures are presented as formal structures for representing decision-making systems. This model can offer an overall picture to the commander of mine warfare the following possibilities:

- the existence of minefield;
- the country that laid the mines;
- the mine delivery platform;
- the mine location;
- the kind of mines laid in the minefield; and
- decisions concerning MCM deployment.

The outcomes of the specific event possibilities were determined by calculations which will be described in Chapter IV. The probabilistic inference network can handle information processing tasks with the following advantages:

- pieces of information are available at various levels of certainty and completeness;
- there is a need for optimal or nearly optimal decisions;
- there may be a need to justify the arguments in favor of the leading alternative choices; and

- general rules of inference (either based on scientific theory, or simply heuristic) are known or can be found for the problem.

Usually there must also be an economic need for the application of these techniques to a problem domain. Accurate models for complex phenomena take a significant effort to develop, even with the help of experts.

Listed below are some examples of actual or potential areas of practical application of inference networks:

- medical diagnosis;
- fault diagnosis in machines and computer software (including automobiles, airplanes, computers, spacecraft, etc.);
- mineral prospecting;
- criminal investigations;
- military strategy formulation (including war-time decision-making);
- marketing strategy and investment; and
- decision-making in design processes (e.g., software design, suspension bridge design, VLSI circuit design).

C. ORGANIZATION OF THE THESIS

Chapter II introduces mine warfare, expert systems, and fuzzy logic. Chapter III discusses the design process of the probabilistic inference network. Chapter IV presents the results of the simulation of mine warfare inference network that can be supported by the certainty factors. Chapter V concludes the thesis work and recommends future efforts.

II. GENERAL BACKGROUND

In Chapter I, mine warfare was dipicted as a constant struggle between the mine designer and MCM. The problem is that without sufficient information about the minefield, clean up is difficult. In order to find a proper method to help the commander make a decision from the incomplete, inexact, or uncertain knowledge and information, fuzzy logic (FL) systems use uncertain or probabilistic knowledge to account for real uncertainties. In this thesis, FL is incorporated with an expert system application.

This chapter introduces the required background of this thesis for designing the probabilistic inference networks. They are mine warfare, expert systems, and FL.

A. MINE WARFARE

Mine warfare has been divided into four parts: types of mines, MCM, the mine delivery, and the minefield planning.

1. Types of Mines

Mines can be divided into two main categories: [Ref. 2:p. 2-2]

a. The Controlled Mine

A mine which after laying can be controlled by the user. The degree of control is generally the ability to make safe or live or to fire the mine at a particular moment.

b. The Independent Mine

A mine which is not controlled. They are operated automatically by some device activated by the presence of ship.

An independent mine can be:

(1) A Contact Mine. A mine which is fired by physical contact with the target.

(2) An Induced Mine. A mine actuated by the effect of a ship on some physical condition in the vicinity of the mine or on radiations emanating from the mine. There are three basic types of the induced mines:

- The magnetic mine. This mine is actuated by the passage of a metal-hulled ship which causes a disturbance of the vertical component of the earth's magnetic field.

- The acoustic mine. The acoustic exploder mechanism is equipped with hydrophones to detect the noise made by the ship's machinery.

- The pressure mine reacts to the phenomenon that a ship in shallow water creates two pressure waves on the sea bottom, separated by a low-pressure (null) area.

Mines can also be constructed with a combination of two or more of the basic influence mechanisms. These types are given a name, *The Combination Mine* ; each influence criterion must be satisfied for mine detonation to be possible.

(3) A Moored Mine. A mine of positive buoyancy held below the surface by a mooring attached to a sinker on the bottom.

(4) A Ground Mine. A mine with negative buoyance which remains on the sea-bed.

(5) A Drifting Mine. A buoyant or neutrally-buoyant mine, free to move under the influence of wind or tide. It may be attached to a small baulk of timber or other innocent-looking object.

(6) An Oscillating Mine. A drifting mine which maintains its depth by means of a hydrostatic depth control mechanism which causes it to oscillate about a set depth.

(7) A Creeping Mine. A buoyant mine held below the surface by a weight, usually in the form of a chain, which is free to creep along the sea-bed under influence of stream or current.

(8) A Mobile Mine. A mine with propulsion equipment like a torpedo, which sinks at the end of its run to become a ground mine.

(9) A Homing Mine. A mine with propulsion equipment which homes on to a target. The mine normally lies on the sea-bed or is secured to a sinker, and is set in motion by a ship influence.

(10) A Rising Mine. A mine having positive buoyancy which is released from a sinker by a ship influence. The mine may fire by contact, hydrostatic pressure or other means.

(11) A Bouquet Mine. A mine where a number of buoyant mine cases are attached to the same sinker. When the mooring of one mine case is cut by a sweep, another mine case rises from the sinker to its set depth.

Chapter IV considers only the contact mine and the induced mine as the nodes in the probabilistic inference network for mine warfare.

2. Mine CounterMeasures

This subsection introduces the aim of MCM and the types of MCM.

a. *The Aim of MCM*

The aim of MCMs is to permit warships and merchant vessels to keep to the seas and enter and leave ports, as necessary for the furtherance of the war effort and support of the population, without unacceptable damage or losses from enemy mines. [Ref. 2:p. 1-1]

This aim can be achieved by:

- Preventing the enemy from laying mines.
- Forcing or enticing the enemy to lay his mines in waters which our ships do not need or do not use.
- Causing mines to explode without loss, or with acceptable loss, to shipping by the use of MCM forces.
- Causing the mines to become ineffective by removing them to a safe place or by preventing the firing mechanism from operating.
- Reducing the danger to shipping by confining ships to routes in which enemy mines are scarce or non-existent, either because mines have not been laid there in any quantity or because their number has been reduced by the actions of MCM forces.
- Altering the characteristics of ships, either permanently or temporarily, so that they do not, or are less liable to, actuate mines.

b. *Types of MCM*

MCMs are of three general types:

- Special equipment installed on board ship to prevent the mine's actuating devices from functioning.
- Physically removing, exploding or disarming mines in a minefield before friendly ships transit the field.

- Circumnavigation of the field.

The last requires little comment, because it is obvious that if a minefield's exact location is known, shipping can be routed around it without undue inconvenience.

When it is necessary to use waters known or suspected to be mined, then sweeping or hunting operations are required to clear a channel through which shipping can pass. In shallow, clear waters moored mine may be visible from a boat or a helicopter. Hunting operations consist of locating individual mines and then disarming or destroying them.

(1) Disarming or Removing. Disarming or removing mines is especially hazardous when the same areas are subject to bombing by the enemy, as in the case of Vietnam anchorages and mud flats. Compounding the difficulty is the fact that mines are mostly buried, and require different handling.

Sweeping operations vary with the type of mine. For moored mines, a cable with a paravane device to support the cable at its outer end and to hold it out at an angle to the sweeper is towed through the water. Spaced along the cable are cutting blades which sever the mooring lines of mines encountered. The mines then bob to the surface and can be destroyed by gunfire.

Bottom mines are obviously not vulnerable to this type of sweeping activity. Certain types of influence mines may be destroyed, however, by towing a device to simulate the influence field of a ship and thereby cause the mines to explode. Noise-makers may be used to actuate acoustic mines. A device to create an electromagnetic field sufficient to disturb the vertical component of the earth's magnetic field may be used to actuate magnetic mines. The device can be towed by either ship or helicopter.

The most difficult mine to counter is the pressure mine. The difficulty lies in attempting to create the pressure disturbance of a large moving ship without using a large moving ship. Such sweeping devices are very expensive. It may be worthwhile to note, however, that one mine defense tactic which could be employed is to move ships through a suspected minefield in column so that all but the lead ship would in effect be traversing waters already swept.

(2) Minesweeping. Minesweeping is a slow, expensive and nerve-racking business. It is successful only to some degree. The word sterilized is frequently used to describe a minefield presumably rendered harmless by minesweeping or hunting operations. However, one can never be 100 percent certain that all mines have been destroyed. It is only possible to reduce the probability of ships' being destroyed by mines to a level that is acceptable to the commander responsible for ordering forces into mined waters. Delayed arming devices make it possible for sweeping ships to pass through an area without detecting any mines. Yet, some time after the sweeping ships have passed through, the mines can be become active.

(3) Minehunting. Minehunting is the location of individual mines by ship and/or airborne equipment and/or divers, and their subsequent disposal. As the range of detection and speed of the ship are limited for physical reasons, the time taken for a hunting operation may be minimized by effective mine-watching and accurate navigation. A hunting operation in good bottom conditions is not necessarily longer than a

sweeping operation, especially if mines of high ship counts are used. The surest means of classification and destruction is by examination and countermining by divers. Neutralization of the mine firing mechanism leaving the mine case virtually intact may however be achieved by the dropping of explosive charges close to the mine by surface vessel or helicopter, but an accumulation of "dead" mine cases on the bottom will increase the difficulties of minehunting. This increase will not be so important if the positions of the mine cases can be accurately recorded by precise navigation methods, or marked (as by triplanes) so as to be readily recognizable.

(4) Clearance Diving. Clearance diving forms a part of the minehunting team. These are divers specially trained in underwater location, identification and disposal of mines. They may be used alone, for example in docks and basins, or in conjunction with the operations of minehunting vessels. Tidal currents, poor visibility and lack of mobility render clearance diving operations very slow, but certain areas where minesweeping and minehunting operations using ships are impractical can only be cleared by clearance divers.

(5) Passive Measures. Passive measures on board a ship vary with the type of mine against which the ship is defending. As a defense against magnetic mines, degaussing coils are used to counter the disturbance which a metal ship would otherwise cause in the earth's magnetic field. Some limited defense against acoustic and pressure disturbance is possible. The defence against moored contact mines is to detect the mines by sonar,

helicopter or other visual means, and then maneuver the ship to avoid them.

3. The Mine Delivery

Tactically, we implement the minelayer aspect of the mine warfare. The mine delivery platform's purpose is to carry and lay mines into the minefield. According to their different function, they are surface delivery, submarine delivery, and aircraft delivery.

a. Surface Delivery

Surface delivery is most useful when it is essential to accurately position mines in a minefield and when the enemy forces in the area are weak or nonexistent. In fact, the ship is a typical model of the surface minelayer. The ships have been designed and built to provide storage, servicing and minelaying facilities; nevertheless, the ship is vulnerable to attack by shore batteries, surface, air, or subsurface units.

b. Submarine Delivery

The Germans were the first to utilize the submarine to lay mines covertly under the very noses of their enemy. With mines designed so that they can be launched through the standard torpedo tubes, any attack-type submarine is a potential minelayer. Submarine minelaying is a means of obtaining very accurate positioning with greatly reduced probability that the delivery vehicle will be detected. It would be a mistake, however, to leave the impression that submarines are immune to detection in hostile areas. Submarines are most vulnerable to detection and attack when operating in waters shallow enough to be mineable.

c. *Aircraft Delivery*

Minelaying by aircraft is especially useful in waters controlled by the enemy, even where formidable enemy defenses exist. Aircraft are most useful for replenishment of an already active minefield. Mines may be dropped from most bombers, or even transport aircraft, with very slight changes to existing configurations. The U.S. Air Force B-29 was used effectively for this purpose during World War II. Air-dropped mines are often rigged with parachutes to slow their descent and reduce the impact velocity. The position accuracy of air-drop minefields is generally excellent if they are laid by aircraft with accurate air navigation and computer delivery systems. Some mines may be ineffective because of damage during the drop.

In summary, it is readily apparent that one advantage of mine warfare is that no specially designed vehicles are required for delivery. Any nation with ships, bombers or submarines has a potential minelaying force.

4. Minefield Planning

Obviously, a preliminary consideration in planning a minefield is the mineability of the waters. There are two factors to consider:

- Where the objective is destruction of shipping, it is essential that the plan not be detected by the enemy.

- Where the objective is to deny the enemy use of certain waters, the commander must decide whether the objective justifies the risk to the minelaying force.

Besides the preliminary consideration of mineability, the effectiveness of a minefield is a function of certain other factors:

- Density of enemy shipping traffic.

- Density of mines in the field, which in turn is a function of the number of mines and the area of the minefield.

- Effective area of influence of the mines used.

- The effective influence area of a transiting ship, which is a function of the length of path through the field and the width of the ship's influence area.

Consider the minefield for which the objective is destruction of enemy shipping. One might hope that several ships would blunder into the field before it is identified by the enemy and shipping warned away. However, realistically one can only count on the first mine which is detonated. Thereafter, enemy countermeasures will attempt to render the field useless. Hence, a measurement of effectiveness for such a field is the probability that one ship will be sunk.

Generally, this minefield model is based on the following assumptions:

- Mines have been laid in secrecy and the enemy is unaware of the field's existence.

- Ships traverse the field on one of two known headings, these being parallel but opposite.

- Ships considered as traffic must pass within the outer limits of the field but are equally likely to enter the field at any point between the limits.

- A ship which enters the mine's influence area will detonate the mine with certainty.

- A mine which is detonated will sink the ship with certainty.

In summary, the best of the MCM is to minimize the existence of the probability that any ships will be sunk. This thesis deals with getting rid of the mines and maintaining our shipping route. After the simulation have been done in Chapter IV, the MCM expert will be highly confident to clean up the minefield before friendly ships hit any mines. Therefore, the minefield planning will be divided into three parts, which are the shipping traffic lane, coast, and the nearest point land.

B. EXPERT SYSTEMS

Expert systems technology is widely perceived as AI technology with the most potential for the development of applications that require domain experts' knowledge. Expert systems are computer programs that are equipped with expert knowledge to help users solve problems. For example, an expert system called MYCIN provides expert advice to medical doctors on the diagnosis and treatment of various types of bacterial information [Ref. 3]. MYCIN is considered an "expert" system because its procedures for diagnosing and recommending treatment are modeled after judgmental heuristics employed by human experts. Emulating human expert behavior is often considered an essential characteristic of an expert system. Expert system technology provides a powerful set of tools for developing systems that can generate expert advice to users for solving important and complex problems. The success of an expert system depends: domain selection, selection of expert(s), knowledge acquisition, and problem development. A basic introduction to expert system technology is provided in the following. Virtually all expert systems contain two basic components: a knowledge base and an inference engine, and a user interface.

1. Knowledge Base and Inference Engine

In a knowledge base, domain-specific knowledge is expressed as a set of condition-action pairs referred to as production rules that specify the action to be carried out, if the prerequisite conditions are satisfied. The typical structure of a condition-action system is shown in Figure 2-1.

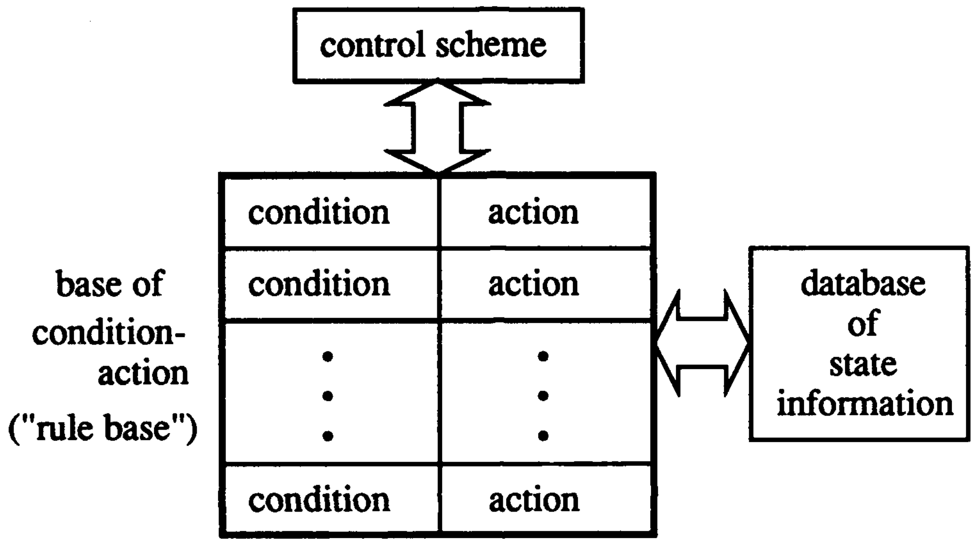

Figure 2-1 The Structure of a Condition-Action System

Expert systems can be described as computer-consultants that emulate human expert reasoning in a problem domain. The process of extracting and encoding domain knowledge held by human expertise is called knowledge engineering. Today, knowledge engineering remains a time-consuming and labor-intensive process wherein a knowledge engineer, must repeatedly interview one or more human experts over a long time period to extract the heuristics to be encoded in the expert system knowledge base. The role of the inference engine is to control the order of rule activation and to update the belief value of the hypotheses based upon acquired evidence.

2. User Interface

A user interface caters to a smooth communication between the user and the system. It may also provide the user with insight into the problem-solving process carried out by the inference engine.

It is convenient to view the inference engine and the interface as one module, usually called an expert system shell, or shell. Figure 2-2 illustrates the basic expert system architecture.

The advantages of separating the knowledge base from the inference engine are listed below: [Ref 4]

- Knowledge can be represented in a uniform fashion (i.e., If...then... style).
- The same inference engine and user interface can be applied to different problem domains (one only needs to add new knowledge).
- It allows modifications of one part without creating side effects in other parts of the code.
- System builders can focus directly on capturing and organizing problem-solving knowledge rather than on the details of low level implementations.
- It allows experimentation with alterative control regimes for the same rule base.

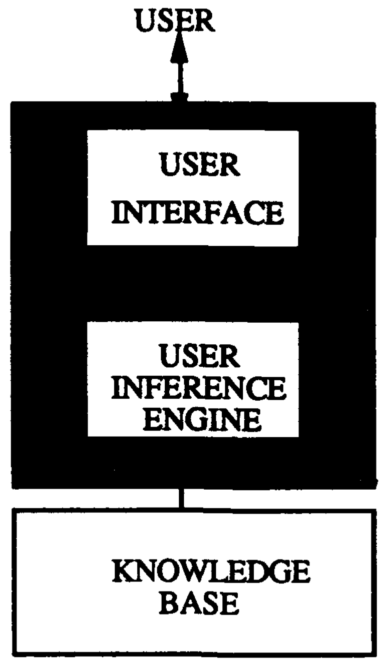

Figure 2-2 A Simplified View of Expert System Architecture

Most expert systems deal with various classes of inference problems, where the expert system must draw conclusions from various evidence or data inputs. In these types of inference problems, the set of rules (see Figure 2-3) can be graphically represented in the form of a set of inference networks. As illustrated in Figure 2-4, an inference network contains top-level hypotheses that are decomposed into various levels of subhypotheses. The subhypotheses, in turn, are further broken down into specific items of evidence, called nodes, that can support these hypotheses. With each node, there is usually an associated prior probability and a rule for combining a subnode prior probability into an updated probability for the node. We will give a detailed description in Chapter III of the interrelationship between node (evidence) and subnode (hypothesis).

IF: The exhaust is smoky, and
The car is backfiring, and
There is a lack of power,
THEN: The carburetor fuel mix is too rich.

IF: There is a lack of power, and
There is a gray deposit on the spark plugs, and
The engine overheats,
THEN: The carburetor fuel mix is too weak.

IF: The carburetor fuel mix is too rich, or
The carburetor fuel mix is too weak,
THEN: The carburetor fuel mix needs to be adjusted.

Figure 2-3 Sample Condition-Action Rules

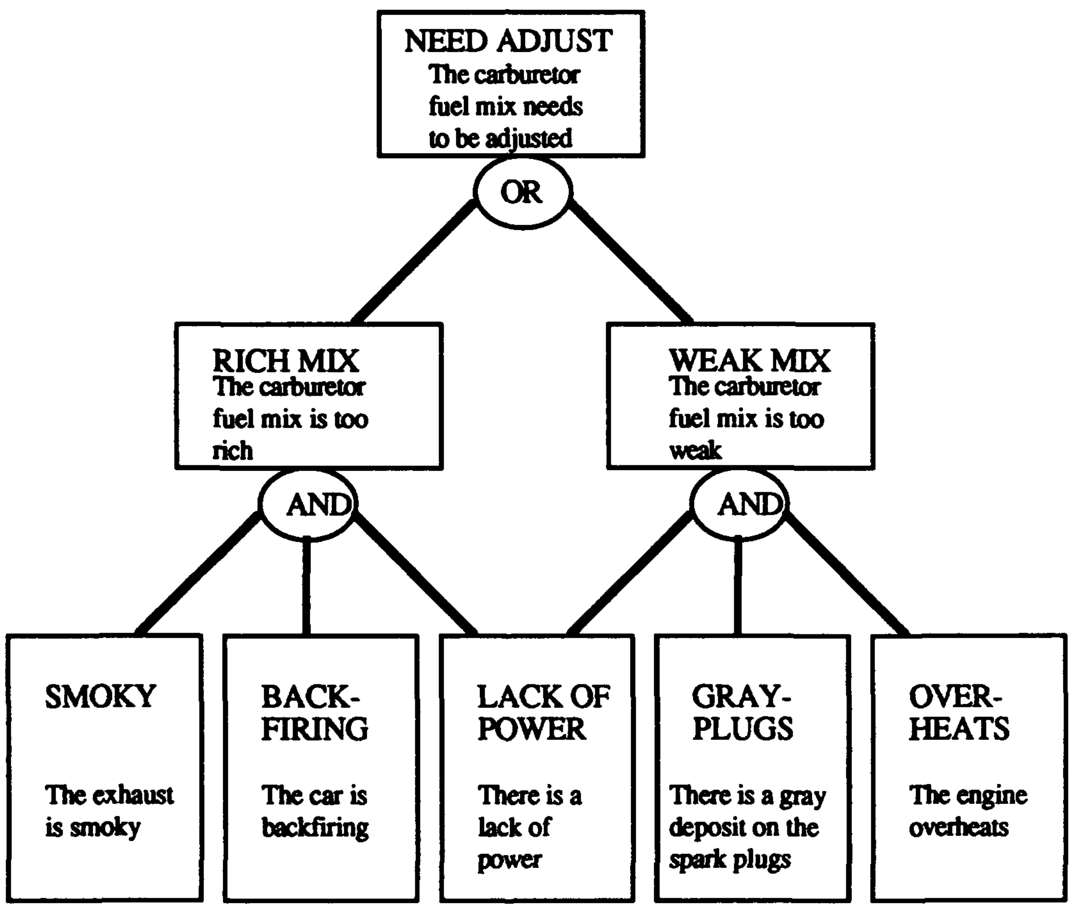

Figure 2-4 Sample Inference Network

C. LISP

In this thesis, we use a C program (Appendix A) to create a knowledge base that is used by the inference network. The inference network is written in LISP.

Commonly used AI languages are LISP and Prolog. The programming language LISP is first implemented at the Massachusetts Institute of Technology (MIT) in the late 1950s under the derection of J. McCarthy [Ref. 5]. LISP is designed specifically for list processing, the manipulation of symbolic information, although it has a capability for numerical data handling as well. LISP uses lambda calculus as a formal, applicative structure with interesting theoretical properties. LISP is especially good for applications in AI and is the most widely used language for this purpose.

LISP gives the programmer great power and flexibility. Data structures are created dynamically without the need for the programmer to explicitly allocate memory. This thesis uses a C program to create a LISP data segment to be used by the inference network code. Declarations for data are not necessary, and a LISP symbol, acting as a variable, may represent one kind of object (e.g., an integer) at one time and a completely different kind of object (e.g., a binary tree) a little later. Using one basic data-structuring concept, the "S-expression," both programs and data are easily represented.

D. FUZZY LOGIC

Logic, according to Webster's Dictionary, is the science of the normative formal principles of reasoning. In this sense, fuzzy logic (FL) is concerned with the formal principles of approximate reasoning, with precise reasoning viewed as a limiting case. In more specific terms, what is central about FL is that, unlike classical logical systems, it aims at modeling the imprecise modes of reasoning that play an essential role in the remarkable human ability to make rational decisions in an environment of uncertainty and imprecision. This ability depends, in turn, on the ability to infer an approximate answer to a question based on a store of knowledge that is inexact, incomplete, or not totally reliable.

Fuzzy Logic enables computers to simulate the ambiguities encountered in real-life situations. The basic idea underlying FL control was suggested in notes published in 1968 [Ref. 6] and 1972 [Ref. 7] and described in greater detail in 1973 [Ref. 8:p. 28-44]. The first implementation was pioneered by Mamdani and Assilian in 1974 [Ref. 9] in connection with the regulation of a steam engine. During the past several years, FL has found numerous applications in fields ranging from elevator control to stock trading. Table 2-1 [Ref. 10:p. 42-44] lists some common products utilizing FL. Amazingly its most important and visible application today is in a realm not anticipated when FL was conceived, namely, the realm of process control [Ref. 11:p. 83-89]. Chapter III gives a detailed explanation of how to use "fuzzy inference rules" to obtain the current probability for each node.

TABLE 2-1 PRODUCTS UTILIZING FUZZY LOGIC

Product	Company	Role of Fuzzy Logic
Elevator Control	Fujitec / Toshiba	Evaluates passenger traffic to reduce waiting time and enhance car announcement accuracy
Golf diagnostic system	Maruman Golf	Selects best golf club for an individual's physique and swing
Video camcorder	Sanyo Fisher / Canon	Determines best focus and lighting when several objects are in picture
Washing machine	Matsushita	Senses quality and quantity of dirt, load size, and fabric type, and adjusts wash cycle
Vacuum cleaner	Matsushita	Senses floor condition and dust quantity and adjusts vacuum cleaner motor power
Hot water heater	Matsushita	Adjusts heating element to correspond to temperature and amount of water being used
Air conditioner	Mitsubishi	Determines optimum constant operating level to prevent power-consuming on-off cycling
Television	Sony	Adjusts screen brightness, color, and contrast
Handheld computer	Sony	Interprets handwritten input for data entry
Auto transmission	Subaru	Senses driving style and engine load to select best gear ratio
Stock trading program	Yamaichi Securities	Manages stock protfolios

III. MATHEMATICAL METHOD

In many practical problem-solving situations the available information is incomplete or inexact. The knowledge is inadequate to support the desired logical inference. However, we can apply generalizations and approximations for transforming our experience into a prediction. This thesis applies Tanimoto's probabilistic inference network [Ref. 5] that allows the expert systems to use uncertain or probabilistic knowledge. We also apply the concept of the FL to solve the inconsistency problem in the inference networks.

This chapter discusses Bayes' rule, probabilistic inference networks, updating probability in inference networks, and certainty factors. Use of these techniques to construct the model for mine warfare is done in Chapter IV.

A. BAYES' RULE

This thesis assumes that the commander wants to know the probabilities that candidate countries have laid mines, given evidence of the existence of a minefield. The following general knowledge may be available: (a) the probability that country-2 has laid mines, regardless of any evidence, (b) the probability that the minefield exists, given that country-2 has laid mines, and (c) the probability that the minefield exists, given that country-2 has not laid mines. In addition, the information of the existent minefield is available. Let H be the hypothesis and E be the evidence listed below:

- H = "Country-2 has laid mines," and
- E = "A minefield has been found."

Thus we have general information:

1. $P(H)$: probability that country-2 has laid mines,

2. $P(E \mid H)$: probability that the minefield is discovered, given that country-2 has laid mines, and

3. $P(E \mid -H)$: Probability that the minefield is discovered, given that country-2 has not laid mines; assuming a minefield exists.

We want the value of $P(H \mid E)$ which represents the probability that country-2 has laid mines, given that minefield is discovered. The $P(H \mid E)$ value can be computed by Bayes' rule:

$$P(H \mid E) = \frac{P(E \mid H)P(H)}{P(E)},$$

where

$$P(E) = P(E \mid H)P(H) + P(E \mid -H)P(-H).$$

To continue the case, we assume the general knowledge of the following values:

$$P(H) = 0.01 \qquad P(E \mid H) = 0.85 \qquad P(E \mid -H) = 0.001.$$

From the formula described above, we can compute

$$P(E) = (0.85)(0.01) + (0.001)(1 - 0.01)$$

which is approximately 0.0095 and

$$P(H \mid E) = (0.85)(0.01) \;/\; 0.0095 = 0.8957.$$

Thus, the probability that country-2 has laid mines, given that the minefield is discovered, is about 0.9. On the other hand, if the minefield is not discovered, the probability that country-2 has laid mines would be

$$P(H \mid -E) = \frac{P(-E \mid H)P(H)}{P(-E)} = \frac{(1 - 0.85)(0.01)}{(1 - 0.0095)}$$

$$= 0.1581.$$

B. PROBABILISTIC INFERENCE NETWORKS

1. Appropriate Domains

Making a decision means choosing among alternative courses of action with or without all the relevant information and often with uncertain information as well. The need for intelligent decision-making is omnipresent in intelligent beings. In people, the need arises at the simple level of choosing whether or not to step around a puddle on a rainy day, or at the complicated level of choosing a treatment plan for a medical patient. Animals need such abilities to find food and evade predators. A mathematician may need to choose from a set of possible directions in which to search for a proof [Ref. 5].

2. Heuristical Elements of Inference Networks

Because of the incomplete knowledge of the conditional probability distribution for the various possible states of evidence, the successful inference network cannot usually be developed directly from Bayes' rule. A reasonable alternative is to develop a hierarchy of "fuzzy" assertions or hypotheses and use substantiated hypotheses at level l to infer hypotheses at level l+1 (see Figure 3-1 and 3-2). Bayes' rule can be used directly to substantiate (establish probability values for) level-1 hypotheses from the observed evidence. Then "fuzzy inference rules" are used to obtain probabilities for other hypotheses, given the evidence.

3. Fuzzy Inference Rules

Fuzzy inference rules are functions for propagating probability values. The general form of such a function is:

$$f : [0,1]^n \longrightarrow [0,1].$$

Thus, a fuzzy inference rule takes an n -tuple of probabilities as arguments and returns a single probability. The truth table and two sets of inference rules for propositional calculus are shown in Table 3-1 [Ref. 5].

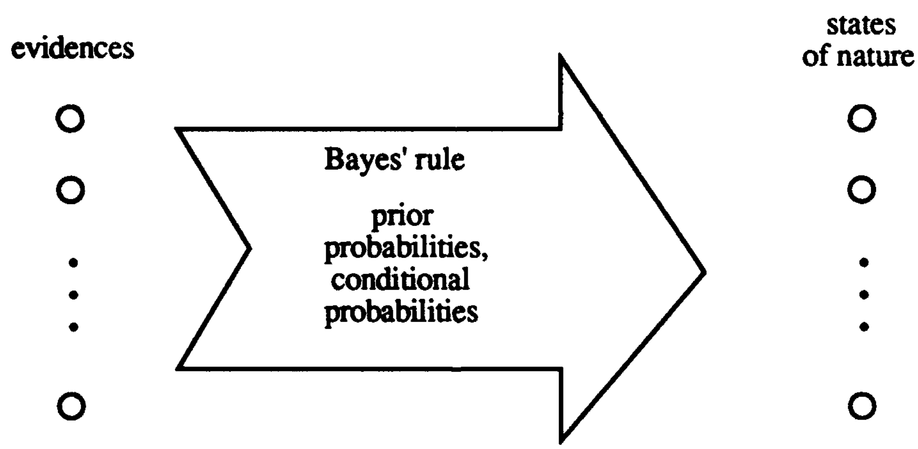

Figure 3-1 Bayes' Rule Application

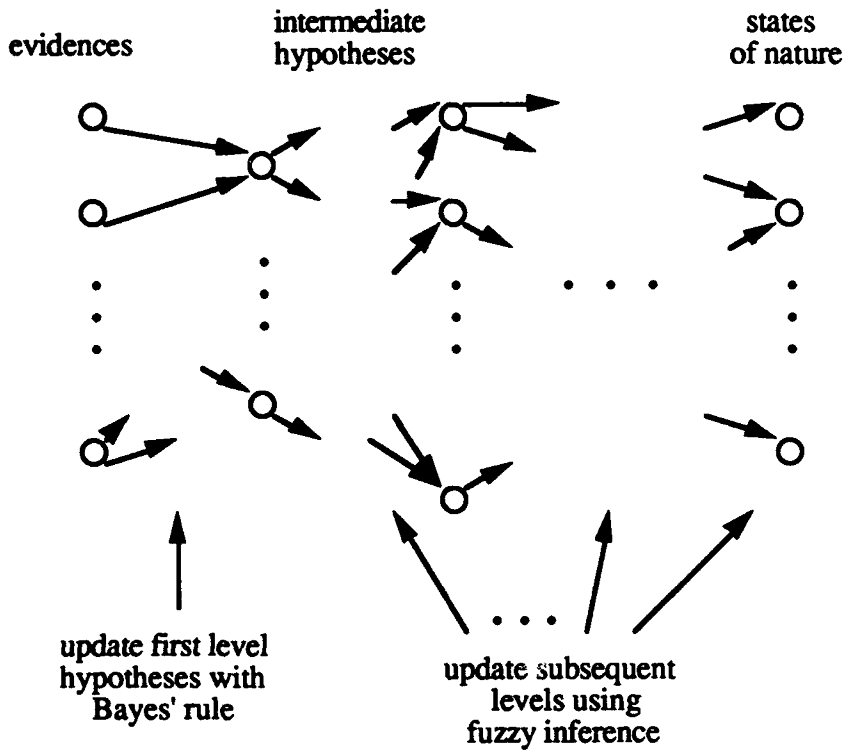

Figure 3-2 Heuristic Inference System

TABLE 3-1 INFERENCE RULES AND TWO FUZZY LOGICS

A	B	-A	A ∧ B	A ∨ B	A -> B	A ⊕ B
F F T T	F T F T	T T F F	F F F T	F T T T	T T F T	F T T F
a	b	1-a	min(a,b)	max(a,b)	max(1-a,b)	xor(a,b)

In Table 3-1, the possibilistic logic rule for A ⊕ B is xor(a,b) = max(min(a,1–b),min(1–a,b)). We use the possibilistic logic or the fuzzy logic in the thesis. Note that the value for A $\wedge$ B in the possibilistic logic is not larger than either the values for A and B.

4. Design of Inference Networks

We assume that relationships and probabilities needed to construct an inference network are provided by an expert, in collaboration either with an AI programmer or with an interactive tool for building expert systems. To design an inference network, the following basic steps are required [Ref. 5]:

- determination of the relevant inputs (i.e., set of possible evidence),
- determination of states of nature or decision alternatives,
- determination of intermediate assertions that may be useful in the inference network,
- formulation of inference links, and
- tuning the probabilities and/or the fuzzy inference functions.

Each of these steps will be explained in sequence. The relevant inputs are usually properties of the object under study. For mine warfare, the relevant input is the likelihood of the existence of a minefield. For the case studied in Chapter IV, if country-1 is known to use submarines to lay mines, then the other mine delivery platforms, the ships or aircraft, may be declared relevant through correlation with the country-1. Relevance determination is non-trivial and requires experts' knowledge. The states of nature are learned from experience or through training. In our case, it is a decision of whether or not to deploy the MCM force.

The intermediate assertions are used to infer the probabilistic network from the relevant inputs to yield the states of nature. Attributes (of the object or situation under investigation) which are not directly observable but probabilistically related to the inputs and states of nature form the basis of intermediate assertions. The nodes for each intermediate assertion or level of mine warfare have been discussed in section A. The intermediate assertions include the country involved in laying mines, the delivery platform used to lay the mines, the location of the mines, and types of mines.

Formulation of inference links may be done on the basis of correlations among attributes. First, a search is made for the simplest logical relationships, and then more and more complicated ones are sought. In order of increasing complexity of relationships we have [Ref. 5]:

- logical concurrence—e.g., an input highly correlated with partial state of nature;
- negative concurrence—strong negative correlation;
- logical implication—whenever A occurs, B does too;
- conjunction—C occurs whenever both A and B occur;
- disjunction—C occurs whenever either A or B occur; and
- exclusive disjunction—either A or B occurs but not both.

Whenever the node(s) for the state of nature has been connected (possibly via intermediate nodes) to the inputs, the inference network topology has been constructed. Probability updating functions still need to be chosen to propagate the effects of inputs throughout the network.

If Bayes' rule is to be used to compute the first-level inference in the network, then there is no need for fuzzy inference rules at that level. But FL updating functions (which are defined later) may be used at subsequent levels to represent the ways information is to propagate through these levels.

Probability values associated with various parts of the network need to be tuned to give reasonable performance. Prior probabilities for states of nature and intermediate assertions must be specified. The conditional probabilities are also essential for Bayesian updating, and they must be well-chosen to give reasonable results. Statistical learning methods might be employed to obtain and to improve probability estimates.

C. UPDATING IN INFERENCE NETWORKS

In an inference network the general format of an inference rule is the following: the statement $P(H \mid E)$ is interpreted "if E, then H," where E is the evidence and H is the hypothesis. In some cases, the evidence may be compounded and instead of E we have $E_1, E_2, \ldots, E_n$ where E_i is the i^{th} piece of evidence bearing on the hypothesis. Each inference rule has a certain strength associated with it, which is the power of the evidence in that rule to confirm the hypothesis in that rule. We now discuss the means for updating probabilities associated with hypotheses on the basis of the certainty with which we know the evidence to be present. The "subjective-Bayesian" updating rules have proved to be useful in expert systems such as PROSPECTOR [Ref. 12:p. 153-167] and will be used in this thesis. We begin by formulating the "odds likelihood" version of Bayes' rule.

1. Odds Likelihood and Bayes' Rule

Bayes' rule is usually formulated as follows:

$$P(H \mid E) = \frac{P(E \mid H)P(H)}{P(E)}.$$

Note that the probability for the negation of the hypothesis can be expressed as:

$$P(-H|E) = \frac{P(E|-H)P(-H)}{P(E)}.$$

Dividing these two equations, we obtain the *odds likelihood* for Bayes' rule [Ref. 5]. An event X having probability P(X) has odds O(X) as:

$$O(X) = \frac{P(X)}{1 - P(X)}.$$

When O(X) is given we can compute P(X) as:

$$P(X) = \frac{O(X)}{1 + O(X)}.$$

We may now express the odds likelihood formulation for Bayes' rule:

$$O(H|E) = \lambda O(H).$$

Here O(H) is *prior odds* on H and λ is defined to be the *likelihood ratio* : $\lambda = P(E \mid H)/P(E \mid -H)$. Thus, we can update the odds on H given the evidence E by the product of the prior odds on H and the likelihood ratio λ.

Apparently, in the construction of an inference network, an expert should provide a value of λ for each rule. In our mine warfare case, an expert should provide $P(E \mid H)$ and $P(E \mid -H)$ for calculating λ and λ' (where λ' will soon be defined.) A C program (see Appendix A) may generate a data segment for the LISP program and calculate λ and λ' on each arc in the inference network. If λ is much greater than 1, the rule has a high strength indicating that the presence of the evidence E makes it much more probable that H is true, that is, $P(E \mid H) > P(E \mid -H)$. In such a case, we may speak of E as being "sufficient" for H. Thus, λ may refer to as a *sufficiency* coefficient for the rule. Otherwise, if λ is close to zero (significantly less than 1), then the presence of the evidence reduces the likelihood of H, and it would be reasonable to say that E is sufficient for –H.

Now, suppose E is false or known to be not present (rather than not known). Then we may write

$$O(H|-E) = \lambda' O(H)$$

where λ' is defined as

$$\lambda' = \frac{P(-E|H)}{P(-E|-H)} = \frac{1 - P(E|H)}{1 - P(E|-H)}.$$

This provides a way to update the odds on H when the information about E is negative. If $0 < \lambda' << 1$, (that is, λ' is between 0 and 1 but much closer to 0 than to 1), then we may say that E is "necessary" for H since the absence of the E (i.e., or the truth of –E) makes H very unlikely. We sometimes speak of λ' as the *necessity* coefficient for the rule.

Continuing with the mine warfare case, we can compute the probability that country-2 has laid mines, given that the minefield exists. Since P(H), the prior probability that country-2 has laid mines, is 0.01, the odds, O(H), is 0.01/0.99 = 0.0101. Thus, λ is $P(E\,|\,H)/P(E\,|-H) = 0.85/0.001 = 850$ and λ' is $(1 - P(E\,|\,H))/(1 - P(E\,|-H)) = 0.15/0.999 = 0.1502$. If we know that the minefield exists, then we compute $O(H\,|\,E) = \lambda O(H) = 850 \times 0.0101 = 8.585$. On the other hand, if the minefield does not exist, we compute $O(H\,|-E) = \lambda' O(H) = 0.1502 \times 0.0101 = 0.0015$. In a probabilistic inference network, an arc may be labelled with a pair of values for λ and λ' to indicate how the presence or absence of the evidence influences the odds on the hypotheses in Figure 3-3.

E represents the fact that the minefield exists, and H represents the fact that country-2 has laid mines.

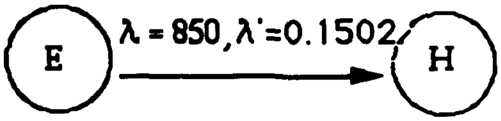

Figure 3-3 Arc in an Inference Network

2. Uncertain Evidence

To extend the discussion from the previous section, we may assume that E above is in fact based on some observations E′ [Ref. 5]. For example, if we say that we have 80 percent confidence in E given E′, then we can re-express this as $P(E \mid E') = 0.8$. To develop some useful techniques for propagating probabilities, it is helpful to have the following simplifying assumption: knowledge of E with certainty would allow us to forget about the observations E′ for purposes of inferring the hypothesis H. Figure 3-4 shows that the only influence of E′ on H comes through E.

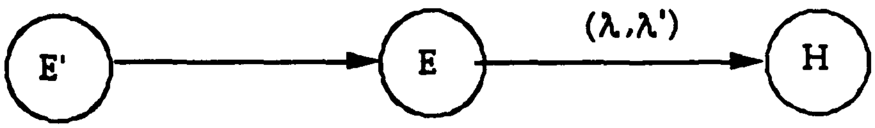

Figure 3-4 Inference with Uncertain Evidence

To determine $P(H \mid E')$ we can interpolate the two extreme values ($P(H \mid E)$ and $P(H \mid E')$) using the conditional probability for E given E′ as shown in Figure 3-5. Taking $P(E \mid E')$ as the value t in the range [0,1], yields:

$$P(H \mid E') = t \times P(H \mid E) + (1 - t) \times P(H \mid -E).$$

Note that when t = 0, P(H | –E) implies P(H | E′) or E′ disprove H, and when t = 1 P(H | E) implies P(H | E′) or E′ suggests H.

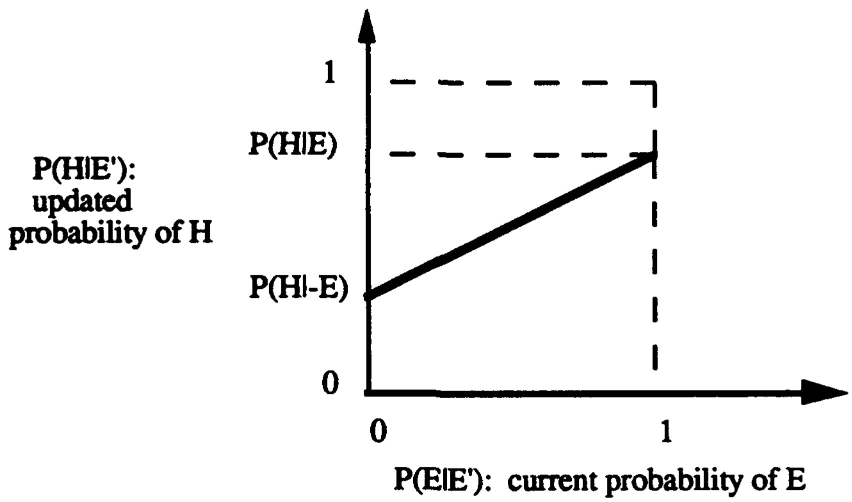

Figure 3-5 A Linear Interpolation Function

Considering the mine warfare case, we assume that the minefield investigation is known to have been reported by an unreliable investigator, who takes correct readings 80 percent of the time. Here we have P(E | E′) = 0.8, the probability that the minefield exists (E) given that the investigator claims that the minefield exists (E′). With the linear interpolation equation, we compute P(H | E′), the probability that country-2 has laid mines given that the investigator claims that the minefield exists, as P(H | E′) = 0.8 x 0.8957 + 0.2 x 0.1581 = 0.7481. This probability happens to be about 20 percent lower than (0.8957, see page 25) that for the case in which the investigator is known to be reliable. The choice of a linear function, rather than some curve, is an arbitrary one. A linear function simplifies the updating computations.

3. The Dilemma for Inference Networks

In order to apply Bayes' rule in an inference network, it is necessary for the various prior probabilities in the network to be consistent with one another [Ref. 5]. In the absence of any observations E', if we use the prior probability to compute or 'update' the P(H) we should get the same P(H) given by the expert. However, an expert often gives subjective prior probabilities to various part of an inference network that are not consistent.

We explain a method that allows for the inconsistency. The inconsistency that can arise from the minefield investigator report is illustrated in Figure 3-6. P(H) should correspond to P(E) along the interpolation line. The consistent prior probability of E or $P_c(E)$ that corresponds to P(H) is somewhere to the left or right of the P(E) given by the expert.

It is important to resolve this inconsistency because various forms of irregular conduct need to be avoided. Developers of the inference network systems used in PROSPECTOR [Ref. 12:p. 153-167] and MYCIN [Ref. 3] solved this type of inconsistency by changing the probability update function $P(H \mid E')$ from linear to piecewise-linear. This piecewise-linear function is designed to pass through the points whose coordinates are the prior on E and the prior on H as given by the experts. For example, Figure 3-7 shows the piecewise version that solves the inconsistency situation of Figure 3-6.

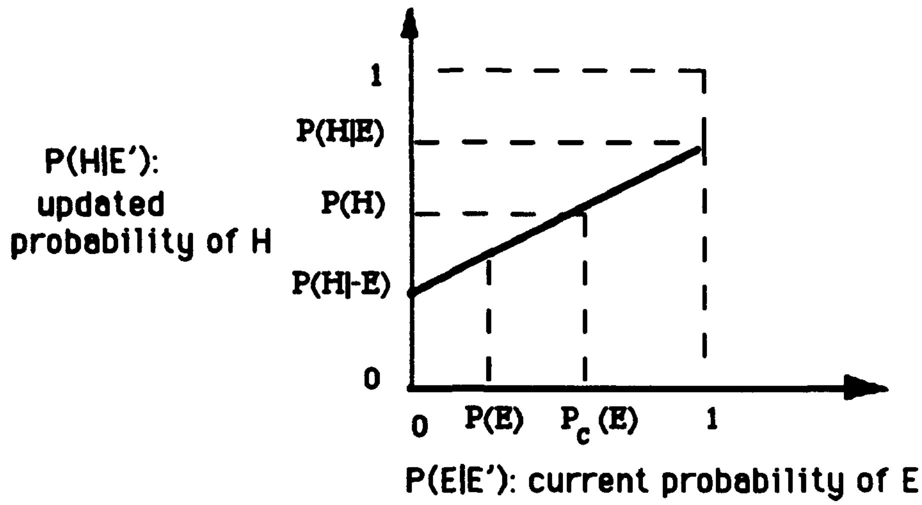

Figure 3-6 Inconsistency in Prior Probabilities for E and H

4. Updating the Probabilities

The function in Figure 3-7 [Ref. 5] provides a good practical mathematical method for updating the probability for an inference. The steps for computing P(H | E') are described as follows.

(1) Compute P(H | E). This step requires O(H) the λ values along the arc from E to H:

$$P(H|E) = \frac{O(H|E)}{1 + O(H|E)} = \frac{\lambda O(H)}{1 + \lambda O(H)}.$$

(2) Compute P(H | –E).

$$P(H|{-E}) = \frac{O(H|{-E})}{1 + O(H|{-E})} = \frac{\lambda' O(H)}{1 + \lambda' O(H)}.$$

(3) Compute P(H | E') from P(E | E') using the function shown in Figure 3-9:

$$P(H|E') = \begin{cases} P(H|{\sim}E) + P(E|E')[P(H) - P(H|{\sim}E)]/P(E) \\ \quad \text{if } P(E|E') \le P(E); \\ P(H) + [P(E|E') - P(E)][P(H|E) - P(H)]/[1 - P(E)] \\ \quad \text{otherwise.} \end{cases}$$

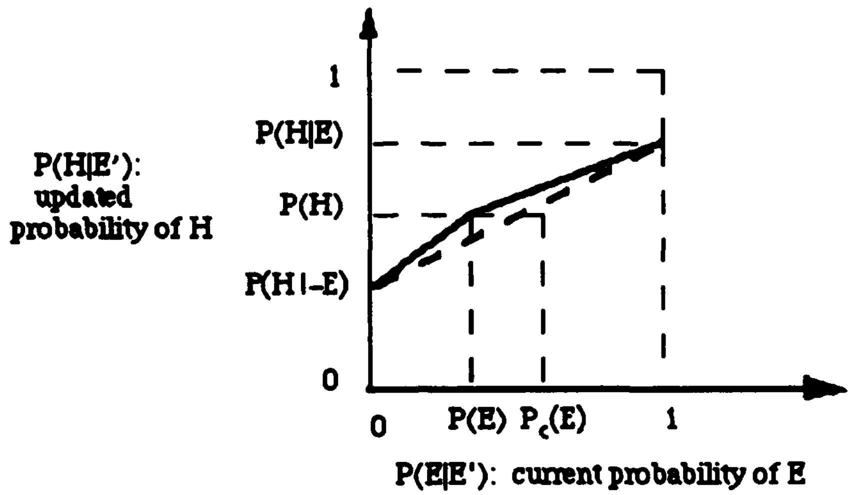

Figure 3-7 Updating the Probability of a Hypothesis

D. CERTAINTY FACTORS

A certainty factor (CF) is a number between –1 and +1 that reflects the degree of belief in a hypothesis [Ref. 3]. Positive CF's indicate there is evidence that the hypothesis is valid. When CF=1 the hypothesis is known to be correct. On the other hand, negative CF's indicate that the evidence suggests that hypothesis is false. The value of every clinical parameter is stored by MYCIN along with an associated CF that reflects the system's "belief" that the value is correct. In MYCIN, CF can be computed by the two measures: "Belief" (MB) and "Disbelief" (MD), defined below:

- MB[H,E] = X means "The measure of increased Belief in the hypothesis H based on the evidence E, is X."

- MD[H,E] = Y means "The measure of increased Disbelief in the hypothesis H, based on the evidence E, is Y."

Recall the subjective probability theory discussed in section III-A, we may argue that the expert's probability P(H) reflects his belief in H. Thus, 1–P(H) can be viewed as an estimate of the expert's disbelief regarding the truth of H. If P(H | E) is greater than P(H), the observation of E increases the expert's belief in H while decreasing his disbelief regarding the truth of H. In fact, MB[H,E] is given by the following:

$$MB[H,E] = \frac{P(H|E) - P(H)}{1 - P(H)}.$$

On the other hand, if P(H | E) were less than P(H), the observation of E would decrease the expert's belief in H while increasing his disbelief regarding the truth of H. MD[H,E] is given by:

$$MD[H,E] = \frac{P(H) - P(H|E)}{P(H)}.$$

Note that one piece of evidence cannot have both favor and disfavor a single hypothesis. If MB[H,E] > 0 then MD[H,E] = 0. If MD[H,E] > 0 then MB[H,E] = 0.

These definitions may be specified in terms of conditional and a priori probabilities:

$$MB[H,E] = \begin{cases} 1 & \text{if } P(H) = 1, \\ \dfrac{\max[P(H|E),P(H)] - P(H)}{\max[1,0] - P(H)} & \text{otherwise.} \end{cases}$$

$$MD[H,E] = \begin{cases} 1 & \text{if } P(H) = 0, \\ \dfrac{\min[P(H|E),P(H)] - P(H)}{\min[1,0] - P(H)} & \text{otherwise.} \end{cases}$$

Note that here P(H) is used to denote a priori probabilities. The CF is defined in terms of MB and MD as:

$$CF[H,E] = MB[H,E] - MD[H,E].$$

In the next chapter, we will explain how the CF value may reenforce our confidence in the fuzzy inference model. Chapter IV simulates the inference network also. The network includes the nodes name, prior-probability, current-probability, and arc expressions. On the other hand, we compute the CFs from the input probabilities and then we use the CFs to confirm the current probability for each node in the network. The CF approach may give the commander an alternate view of the problem.

IV. AN INFERENCE NETWORK

Chapter III derived the equation for computing $P(H \mid E')$ from $P(E \mid E')$. To illustrate this technique for subjective-Bayesian inference in mine warfare, we consider the problems occasionally faced by the commander in war time.

From Chapter I, the problems that concern the commander in mine warfare are the following:

- Do the minefields exist?,
- Which country will lay the mines?,
- What delivery platform will lay the mines?,
- Where are the mines?,
- What kind of mines are they?, and
- Do we need to deploy the MCM forces?.

These kinds of problems are fuzzy, and there must accordingly be some arbitrariness in any method for them. The method presented here is one of many possibilities; it embodies one of the many possible sets of heuristics for predicting whether or not to deploy the MCM force on the basis of pre-mission observations.

This chapter explores the heuristics for mine warfare evaluation, the implementation of LISP and C programs, the results of the simulation, and the conclusions of the certainty factors.

A. HEURISTICS FOR MINE WARFARE EVALUATION

The diagram showing all the nodes and arcs of the probabilistic inference network for our problem is shown in Figure 4-1. The prior probabilities on nodes are not shown, but are given in Appendix B and Appendix C, as are the λ and λ' values for each arc. Detailed descriptions of these nodes and arcs are given in the following paragraphs.

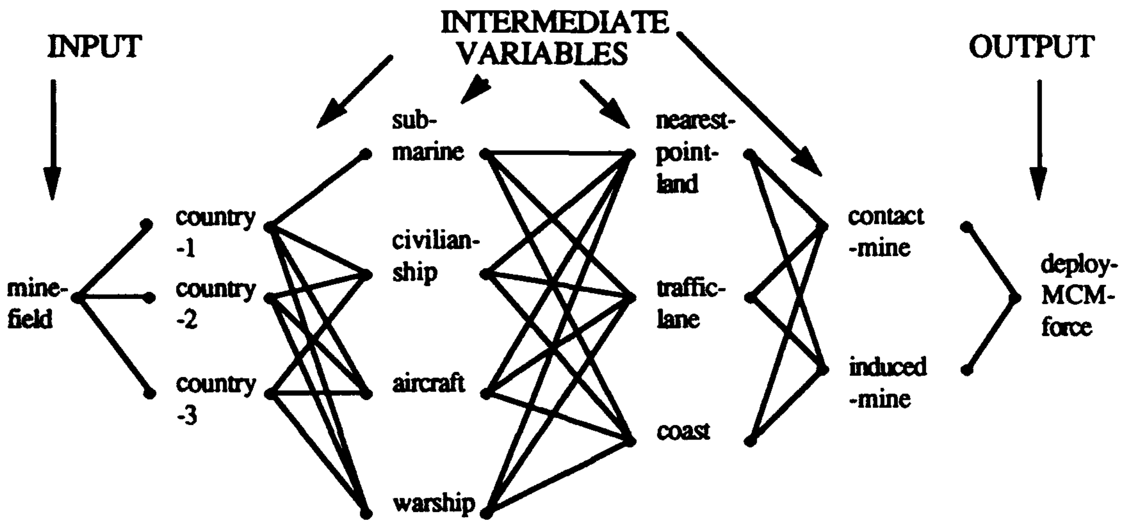

Figure 4-1 Probabilistic Inference Network for Mine Warfare Problem

Before actually using a sea area to carry out the operational mission without consideration of the threat by other enemy's weapons, there is one important weapon we can not neglect—mines. "Do the minefields exist?", is becoming the commander's biggest concern. Normally, the belligerents will know whether or not the minefields exist by means of the announcement of the minelayer or the report of the mine investigator.

In Figure 4-1, the main variable to be predicted is the deploy-MCM-force of mine warfare. This comprises such features as contact-mine and induced-mine. Since it cannot be known for certain whether the sea area has been mined, the inferences we make about whether or not to deploy the MCM force can be probabilistic at best. Since it is difficult to know the statistical relationships among these variables with any degree of accuracy, the results cannot even represent true probabilities. All we can say is this: our system will incorporate the judgment of an imaginary "expert."

Since the input variable, mine-field, can conceivably affect our estimate of the MCM force deployment, we shall design a network in which the various tactical concerns are inputs and the final node corresponds to deploy-MCM-force. To simplify the relationships between input and output to the point where we can rationally model them, we introduce a number of intermediate variables as shown in Figure 4-1. The relationships between input and intermediates, between intermediates and other intermediates, and between intermediates and output are easier to understand and describe than the relationship from input directly to output. In our case, the input is the mine-field, and we introduce a set of three "first intermediate variables" as intermediates: country-1, country-2, and country-3. These are predicted directly from the input variable. A set of four "second intermediate variables" are: warship, civilian-ship, aircraft, and submarine. These are predicted directly from the first intermediate variables. A set of three "third intermediate variables" are: nearest-land-point, traffic-lane, and coast. These are predicted directly from the second intermediate variables. A set of two "fourth intermediate variables" are: contact-mine and induced-mine. These are predicted directly from the third intermediate variables. The output is deploy-MCM-force, which finally is predicted directly from the fourth intermediate variable.

In the following section implements the main program LISP and the program C, to simulate the variable shown in Figure 4-1. The nodes and interrelative arcs data are be inputted by the user into the C program.

B. IMPLEMENTATION OF LISP AND C PROGRAMS

The most important function in LISP is called UPDATE-PROB shown below, it uses the formula on page 38 to compute a proper current probability of H. UPDATE-PROB computes P(H | E') for a single arc.

```
(defun update-prob (h arc)
  (cond
    ((> (current-prob (car arc))
        (prior-prob (car arc)))
     (report-progress 'supportive h arc)
     (+ (prior-prob h)
        (* (/ (- (prob (* (sufficiency arc)
                          (prior-odds h)))
                 (prior-prob h))
              (- 1.0 (prior-prob (car arc))))
           (- (current-prob (car arc))
              (prior-prob (car arc))))))
    (t (report-progress 'inhibitive h arc)
      (+ (prob (* (necessity arc) (prior-odds h)))
         (* (/ (- (prior-prob h)
                  (prob (* (necessity arc)
                           (prior-odds h))))
               (prior-prob (car arc)))
            (current-prob (car arc)))))))
```

In the following functions, we define supporting functions UPDATE-PROB. They include the function REPORT-PROGRESS, the function ODDS, and the function PROB.

The function REPORT-PROGRESS helps to show the progress of computation through the inference network. This function is outlined below.

```
(defun report-progress (supp-inhib h arc)
  (cond
    ((null reporting) nil)
    (t
      (format t "~%~a probability updating for node ~a"
              supp-inhib h)
      (format t " along arc:~%~s with prior odds ~s."
              arc (prior-odds h))
      (format t "~%Prior and current probs of Evidence are ~s and ~s."
              (prior-prob (car arc)) (current-prob (car arc)))
```

The functions ODDS and PROB convert between probability values (given by an expert in Appendix B) and odds. The function ODDS was mentioned in Chapter III. Representation of ODDs in LISP is shown below:

```
(defun odds (prob)
  (/ prob (- 1.0 prob)))
```

The function PROB was also mentioned in Chapter III. Representation of PROB in LISP is shown below:

```
(defun prob (odds)
  (/ odds (1+ odds)))
```

The following function helps create the representation of the network by entering values onto the property list of the node to get from the execution of the C program, as is shown in Appendix C. The form of the argument list is this: L = (*atom prior-probability current-probability arc-expression*). The last argument to DEFINE-NODE is an "arc expression," that describes the incoming arcs and how their effects are to be combined.

```
(defmacro define-node (name prior-prob current-prob arcs)
  '(progn
```

```
(setf (get ',name 'prior-prob) ,prior-prob)
(setf (get ',name 'prior-odds) (odds ,prior-prob))
(setf (get ',name 'current-prob) ,current-prob)
(setf (get ',name 'current-odds) (odds ,current-prob))
(setf (get ',name 'arcs) ',arcs)))
```

The following functions will abbreviate the operations for accessing property lists and accessing components of arc expressions.

```
(defun current-prob (n) (get n 'current-prob))
(defun prior-prob (n) (get n 'prior-prob))
(defun current-odds (n) (get n 'current-odds))
(defun prior-odds (n) (get n 'prior-odds))
(defun sufficiency (arc) (cadr arc))
(defun necessity (arc) (car (cddr arc)))
```

To combine the independent evidence effectively, it is necessary to know the effects of the lambda values along each incoming arc, so that these can be multiplied to get an overall lambda value. The next function determines an effective lambda value.

```
(defun effective-arc-lambda (arc)
  (/ (odds (update-prob h arc))
     (prior-odds h)))
```

The function COMBINE-INDEP-LAMBDAS actually multiplies the effective lambda values together to combine their effects.

```
(defun combine-indep-lambdas (arc-exp)
  (apply #' *
         (mapcar #' eval-arc-exp
                 (cdr arc-exp))))
```

The following functions represent the conjunctive arc expression and the disjunctive arc expression.

The function COMBINE-CONJUNCTIVE-LAMBDAS is returning the smallest of the effective lambda values of the arc subexpressions.

```
(defun combine-conjunctive-lambdas (arc-exp)
  (apply #' min
         (mapcar #' eval-arc-exp
                 (cdr arc-exp))))
```

The next function COMBINE-DISJUNCTIVE-LAMBDAS is returning the largest of the effective lambda values of the arc expressions.

```
(defun combine-disjunctive-lambdas (arc-exp)
  (apply #' max
         (mapcar #' eval-arc-exp
                 (cdr arc-exp))))
```

The function UPDATE-NODE updates the current odds and probabilities of all nodes, that is, the nodes on the list TEST except the mine-field node. The sequence of nodes on the list is important: they must be topologically sorted so that if there is an arc from A to B in the network, then either A precedes B in the list, or A does not appear in the list.

```
(defun update-nodes (nodes)
  (cond ((null nodes) nil)
        (t (update-node (car nodes))
           (update-nodes (cdr nodes)))))
```

The function EVAL-ARC-EXP evaluates an arc expression, finding an effective odds updating factor that takes the effects of all the arcs in the expression into account.

```
(defun eval-arc-exp (arc-exp)
  (cond ((eq (car arc-exp) 'arc)
         (effective-arc-lambda (cdr arc-exp)))
        ((eq (car arc-exp) 'indep)
         (combine-indep-lambdas arc-exp))
        ((eq (car arc-exp) 'and)
         (combine-conjunctive-lambdas arc-exp))
        ((eq (car arc-exp) 'or)
         (combine-disjunctive-lambdas arc-exp))
```

```
(t (print '(illegal arc expression)) (print arc-exp))))
```

The following function causes one node's values to be updated and shows one node's current probability.

```
(defun update-node (h)
  (setf (get h 'current-odds)
        (* (prior-odds h)
           (eval-arc-exp (get h 'arcs))))
  (setf (get h 'current-prob) (prob (current-odds h)))
  (format t "~%current probability of node ~a is ~s.~%"
           h (current--prob h)))
```

Finally, to start running our simulation, we can run the LISP program as follows:

```
(load 'mcm)
(setq reporting t)
(test)
```

C. THE SIMULATION RESULTS

We now explain the simulation steps shown in Figure 4-2. A C program mcm.c takes expert's imputs for constructing inference network: nodes name, prior-probability and current-probability for each node, arc expression including the atoms name and the necessary conditions P(E | H) and P(E | –H) for computing sufficiency and necessity. Appendix B lists a sample usage session of *mcm.c* while Appendix C lists the corresponding output. This output from mcm.c would be the data segment, *mcmdata.c* , for the LISP inference network.

For simulation, we load the inference network *mcm.l* into the LISP interpreter. A detailed simulation run is in Appendix D. We will concentrate on the current probability of each node at the last line of each block. For example, in the simulation results, current probability of node country-2 is as follows:

inhibitive probability updating for node country-2 along arc:
(mine-field 850.0 0.1502) with prior odds 0.0101010101010101.
prior and current probs of evident are 0.9 and 0.5.
Current probability of node country-2 is 0.006228832619601373.

The same things will be shown for the rest of the nodes in Appendix D.

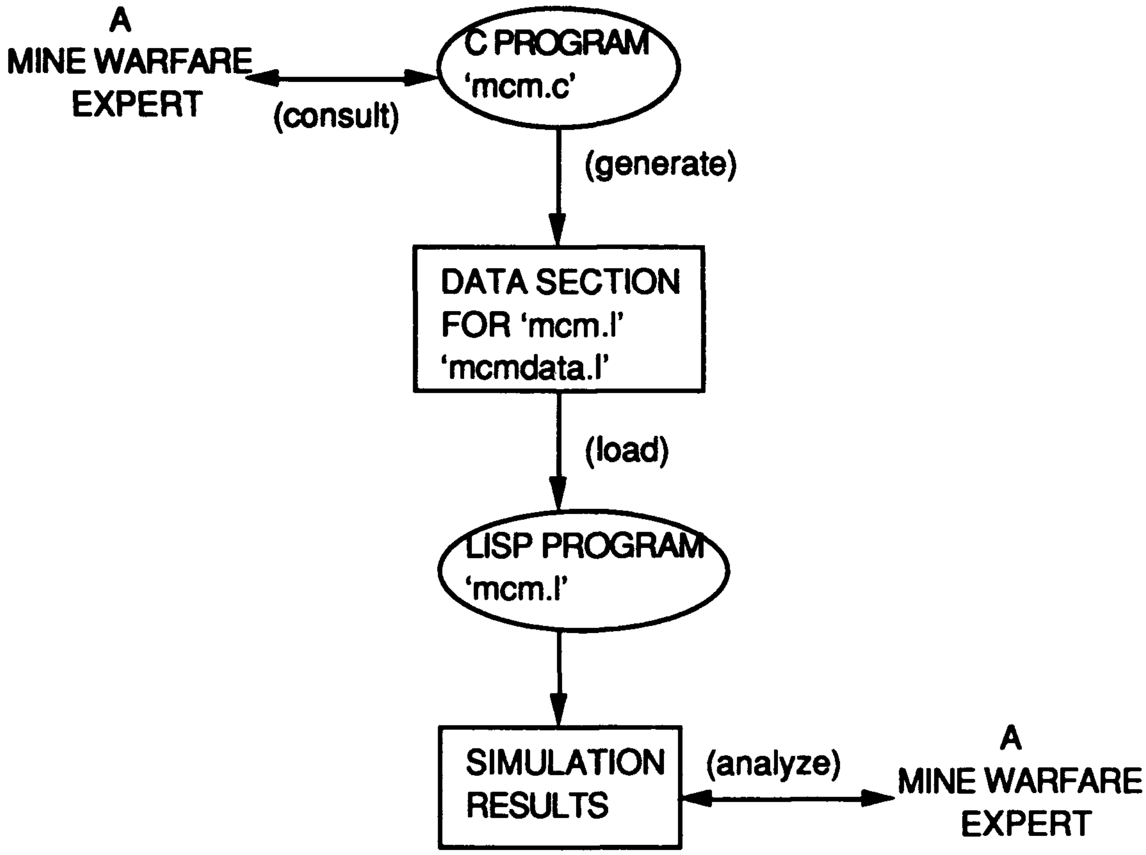

Figure 4-2 The Procedure to Simulate the Programs

Table 4-1 summarizes the simulation results from Appendix D. Analyzing the results and investigating the degree of confidence gives the possible value for deploying the MCM forces.

TABLE 4-1 SUMMARY OF THE SIMULATION RESULTS

Node Name	The Current Probability of Node
deploy-MCM-force	0.6568
induced-mine	0.7229
contact-mine	0.8970
coast	0.7371
traffic-lane	0.7694
nearest-point-land	0.4616
warship	0.6094
aircraft	0.2896
civilian-ship	0.3039
submarine	0.4667
country-3	0.3966
country-2	0.0062
country-1	0.7979

In Table 4-1, the current probabilities of each node taken from Appendix D are sorted in reverse order of the inference network levels. Combined with Figure 4-1, comparison of the current probabilities of the nodes at the same level, we have the following conclusion.

For this mine warfare scenarios, based on the analysis, we have a confidence degree of 0.6568 to suggest that the commander deploy MCM forces. The MCM forces may confront the threat of contact mine, or even the threat of induced mine. Owing to the assumption of this task, the enemy may possibly, first, lay mines in the traffic lane of our fleet; secondly, in the coast; and finally at a nearest land point that is an aid to navigation. The enemy will probably use in descending order warships, civilian ships and finally airplanes to lay mines. Country-1 may consider using submarines to lay mines, because it is safer. The countries that might lay mines are country-1, country-3, and country-2, in that order. However, in order to defend herself, country-2's probability of laying mines increases. If there are mines in the traffic lane and neither country-1 nor country-3 laid the mines, then either country-2 laid them or they are residual mines from the past. Therefore, to avoid being hit by mines, our fleets are strictly prohibited from entering the waters until they are cleaned up by our MCM forces.

D. COMMENTS ON THE CERTAINTY FACTOR

As mentioned in Chapter III, the CF can be computed by the definitions of Bayes' rule, MB, MD, and CF after we input the necessary probabilities. Table 4-2 sort the results of the CF for the relationship between H and E in Figure 4-1.

TABLE 4-2 SUMMARY OF THE CERTAINTY FACTOR

Hypotheses	Evidences	Logic Condition	Certainty Factors
country-1	mine-field	independent	–0.9693
country-2	mine-field	independent	0.8946
country-3	mine-field	independent	–0.2958
submarine	country-1	independent	0.7297

civilian-ship	country-1 country-2 country-3	independent independent independent	–0.9650 0.9980 0.7059
aircraft	country-1 country-2 country-3	independent independent independent	–0.9764 –0.4444 –0.9979
warship	country-1 country-2 country-3	independent independent independent	0.9301 0.9980 –0.9540
nearest-point-land	submarine aircraft	independent independent	–0.9964 –0.6667
nearest-point-land	civilian-ship OR warship	disjunctive	0.8077
traffic-lane	submarine OR civilian-ship OR warship OR aircraft	disjunctive	0.9982
coast	submarine aircraft	independent independent	0.6774 –0.2857

coast	civilian-ship OR warship	disjunctive	0.9833
contact-mine	traffic-lane	independent	0.9862
contact-mine	nearest-point-land OR coast	disjunctive	0.8644
induced-mine	traffic-lane	independent	0.8077
induced-mine	nearest-point-land OR coast	disjunctive	0.7825
deploy-MCM-force	contact-mine OR induced-mine	disjunctive	1.0

The notation CF[H,E] = X is used to represent the CF for the hypothesis H based upon evidence E. For example, the last hypothesis and evidences in Table 4-2 are expressed:

H = To deploy the MCM force,
E1 = The mine is the contact mine,
E2 = The mine is the induced mine.

Thus CF[H,E1VE2] = 1.0, this sample hypothesis above may be qualified as follows:

CF[H,E1VE2] = 1.0 : There is definite (1.0) that to deploy the MCM force.

The rest of the CF[H,E] value is listed in Appendix E.

From the above discussion, we conclude that Tanimoto's method [Ref. 5] is consistent with MYCIN's method [Ref. 3]: both methods resolve the inconsistency by the piecewise linear equations for updating the probabilities instead of using a linear equation. In this chapter, we showed that MYCIN and Tanimoto's method are different: Tanimoto computes the current probability for each node and MYCIN compute the value of CF for each node. For example, Table 4-1 has a confidence degree of 0.6568 to suggest that the commander deploy MCM forces by the current probability of the deploy-MCM-force node. From the Table 4-2, CF[H,E1VE2] = 1.0 means that it is definite (1.0) to deploy the MCM force based upon the disjunctive evidence: mines are contact mines (E1) OR the mines are induced mines (E2). This CF value (1.0) enhances the determination obtained by Tanimoto's method (original value of 0.6568) of the commander to deploy the MCM forces. In other words, CF and Tanimoto's methods could be treated as complementary.

V. CONCLUSIONS

This thesis focuses on use of the probabilistic inference networks in an expert system to make decision regarding mine countermeasures. Implemented in LISP and C, this intelligent mine warfare expert system is capable of assisting the commander in making efficient and accurate decisions in mine warfare.

A. SUMMARY

Chapter I described the use of probabilistic inference networks to solve MCM deployment problems and the objectives of building such a network system. Chapter II discussed the required backgrounds for the thesis, including mine warfare, expert systems, and FL. Description of the mathematical model and the certainty factors for the thesis was accomplished in Chapter III. In Chapter IV, the mathematical model was translated into LISP and the CF values were computed; a code for LISP was created by a C program that takes parameters from the user. Chapter IV showed the simulation results. A commander can analyze the simulation results so that he can make a decision whether to deploy MCMs forces.

B. FUTURE WORK

Many researchers have shown that the tactical knowledge, reasoning, and decision-making process during war time can be modelled by condition-action rules and associated expert systems. This thesis uses probabilistic inference networks to investigate MCM deployment. To develop a reasonable mathematical model and to obtain accurate simulation results for mine warfare in the future, the following efforts necessitate further studies:

- To gather a better or complete mine warfare chronicle for better evaluation of λ and λ'.

- To develop the fuzzy tools such as: fuzzy processor, micro-computer code, and to use fuzzy logic to manage mine warfare.

- To use a LISP machine that can help us to execute LISP program efficiently.

APPENDIX A. C PROGRAM

```
/*
     The purpose of this program, mcm.c, is for the user to create
     a data file named mcm.l. The user inputs the parameters :
               1. The number of levels,
               2. The number of nodes in each level,
               3. The current node name,
             4. The prior-probability and current-probability
                for each node, and
               5. The interrelationship of atoms wihtin node such as :
                    (1). The number of atoms,
                    (2). The atoms' name for each courrent node,
                    (3). The probability for calculating SUFFICIENCY
                         and NECESSITY.
     The probabilistic inference network should be obtained from an expert.
     A complete node looks like :
               (define-node node-name prior-probability
               current-probability arc-expression)
 */
#include <stdio.h>
#include <strings.h>

#define fname_len 10
#define newline  fprintf(fp,"\n")
#define MAXlevel 10
#define MAXtest  256
#define IsDigit(x) ((060 <= x) && (x <= 071))
#define FALSE 0

char invite[] = "Enter probability for calculating sufficiency and necessity :
\n";
char invite_atoms[] = "Enter the atoms name :\n";
char invite_arcs[] = "Enter the number of arcs :\n";
char defuntest[MAXtest];
char atom[20], node[20];
char nth[MAXlevel+ 1][5] ={
        " ", "1st", "2nd", "3rd", "4th", "5th", "6th",
        "7th", "8th", "9th", "10th"};

int NofArc, NofNode, NsingleArc, NconjArc;
float ls,ln;

main(argc,argv)          /* Main programm start from here. */
int argc;
char **argv;
{
```

```
FILE *fp;          /* To create a file to store the data of th node. */

int level, node_in_level, k,o,l,m;
int NofLevel;

char lit[5],lit1[5],lit2[3];
/* lit[] is either null or indep.
                        lit1[]: yes, no, 0.
                        lit2[]: and, or, 0.        */
        char filebase[fname_len], Nofnode[4], Nsinglearc[4], Nconjarc[4];

        float prior_prob, current_prob;

        strcpy(defuntest,"(defun test() (update-nodes '(");
        strcpy(filebase, argv[1]);    /* first argument is the file name */
        strcat (filebase,".l");       /* To create a file named fn.l. */

        fp = fopen (filebase,"w");    /* Open and write the file, we create it.
        */

           NofLevel = atoi(argv[2]);     /* 2nd argument is the number of levels.
        */

        for (level=1; level<=NofLevel; level++)
           {

             printf ("\nEnter the number of nodes in %s level :\n"
,nth[level]);
             scanf ("%s", Nofnode);

             while (!IsDigit(Nofnode[0])) {    /* Need numeric in here. */
        printf ("Input Error!!\n");
        printf ("Enter the number of nodes in %s level :\n",nth[level]);
        scanf ("%s",Nofnode);
}

NofNode = atoi(Nofnode);
for (node_in_level=1; node_in_level<= NofNode; node_in_level++)
{

        printf ("Enter the current node name :\n");
        scanf ("%s",node);

        while (IsDigit(node[0])) {    /* Need char in here. */
                printf("Input Error!!\nEnter the current node name :\n");
                scanf ("%s",node):
        }
```

```
printf ("Enter the prior-prob and current-prob:\n");
scanf ("%f %f",&prior_prob,&current_prob);
fprintf(fp,"(define-node %s %.4f %.4f ",
node,prior_prob,current_prob);

if (level == 1)  fprintf (fp, "())\n");
else {
        newline;
        printf ("Do you have 'and' or 'or' branch :(yes/no)\n");
        scanf ("%s",lit1);

        while(IsDigit(lit1[0])) {
                        printf("Input Error!!\n");
                        printf("Do you have 'and' or 'or' branch :
(yes/no)\n");
                        scanf ("%s",lit1);
                }

                if (!strcmp(lit1,"no")) {
                        /* no AND/OR arcs; yes I have indep arcs */
                        IsNumeric ();    /* Need numeric in here. */
                        fprintf (fp," (indep\n");

                        for (k=1; k<=NofArc; k++) {
                                likelihood();
                                fprintf (fp,"  (arc: %s %.4f %.4f)\n"
,atom,ls,ln);

                                if (k == NofArc){
                                        fprintf(fp," )\n");
                                        fprintf(fp,")\n");
                                }
                        } /* end for k<= NofArc */
                } /* end if lit1 = 'no' */

                else {
                        fprintf (fp, " (indep \n");
                        printf ("Enter number of arcs except for 'and' or 'or' :\n");
                        scanf ("%s",Nsinglearc);

                        while (!IsDigit(Nsinglearc[0])) {  /* Need numeric
                        in here */
                                printf("Input Error!!\n");
                                printf("Enter number of arcs except for 'and'
 or 'or' :\n");
                                scanf ("%s",Nsinglearc);
                        }

                        NsingleArc = atoi(Nsinglearc);
```

```
                    for (o=1; o<=NsingleArc; o++) {
                          likelihood();
                          fprintf (fp, "  (arc: %s %.4f %.4f)\n"
.atom.ls.ln);
                    }

                    printf ("Enter the number of 'and' or 'or' :\n");
                    scanf ("%s",Nconjarc);

                    while (!IsDigit(Nconjarc[0])) {  /* Need numeric in
                    here. */
                          printf ("Input Error!!\nEnter the number of
'and' or 'or' :\n");

                          scanf ("%s",Nconjarc);
                    }
                     NconjArc = atoi(Nconjarc);

                     for (l=1; l<=NconjArc; l++) {
                        printf ("Enter 'and' or 'or' :\n");
                        scanf ("%s",lit2);
                        while (IsDigit(lit2[0])) {  /* Need char in here
*/

                              printf("Input Error!!\nEnter 'and' or 'or' :
\n");

                              scanf ("%s",lit2);
                              }
                    IsNumeric ();   /* Need numeric in here. */
                       fprintf (fp,"  (%s\n",lit2);
                       for (m=1; m<=NofArc; m++) {
                              likelihood();
                              fprintf (fp,"   (arc: %s %.4f %.4f)\n",atom.
ls.ln);

                              if (m == NofArc)
                              fprintf (fp, "  )\n");
                              }

                              if (l == NconjArc) {
                               fprintf (fp, "  )\n");
                                fprintf (fp, ")\n");
                              }
                     }  /* end for l<=NconjArc */
             }   /* end the nearest else */
       }               /* end the farthest else */

             newline;

             if (level != 1)
             strcat(defuntest, node);       /* To collect node.
if level isn't equal to 1. */
```

```
                strcat(defuntest, " ");

                }   /* end node_in_level */

        }   /* end level */

        strcat(defuntest, ")))");
        fprintf (fp,"%s \n",defuntest);
        fclose(fp);
        printf ("GoodBye");

} /* end main */


likelihood()        /* This subroutine is calculating SUFFICIENCY and
                    NECESSITY from p1 and p2 given by an expert.   */
{
        float p1,p2;

        printf ("%s",invite_atoms);
        scanf ("%s",atom);

        while(IsDigit(atom[0])) {  /* Need char in here. */
                printf ("Input Error!!5s",invite_atoms);
                scanf ("%s",atom);
        }

        printf ("%s",invite);
        scanf ("%f %f",&p1,&p2);
        /* p1 = prob(E/H) and p2 = prob(E/-H) */
        ls = p1/p2;
        ln = (1-p1)/(1-p2);

}

IsNumeric ()              /* This subroutine is converting char into numeric. */
{

        char Nofarc[4];

        printf ("%s",invite_arcs);
        scanf ("%s",Nofarc);

        while(!IsDigit(Nofarc[0])) {
                printf ("Input Error!!\n%s",invite_arcs);
                scanf ("%s",Nofarc);
        }

        NofArc = atoi(Nofarc);
}
```

APPENDIX B. THE C PROGRAM EXECUTION

```
Enter the number of nodes in 1st level :
1
Enter the current node name :
mine-field
Enter the prior-prob and current-prob:
0.9 0.5

Enter the number of nodes in 2nd level :
3
Enter the current node name :
country-1
Enter the prior-prob and current-prob:
0.7 0.001
Do you have 'and' or 'or' branch :(yes/no)
no
Enter the number of arcs :
1
Enter the atoms name :
mine-field
Please estimate the probability for calculating sufficiency and necessity :
0.01 0.8
Enter the current node name :
country-2
Enter the prior-prob and current-prob:
0.01 0.85
Do you have 'and' or 'or' branch :(yes/no)
no
Enter the number of arcs :
1
Enter the atoms name :
mine-field
Please estimate the probability for calculating sufficiency and necessity :
0.85 0.001
Enter the current node name :
country-3
Enter the prior-prob and current-prob:
0.3 0.01
Do you have 'and' or 'or' branch :(yes/no)
no
Enter the number of arcs :
1
Enter the atoms name :
mine-field
Please estimate the probability for calculating sufficiency and necessity :
0.5 0.8
```

```
Enter the number of nodes in 3rd level :
4
Enter the current node name :
submarine
Enter the prior-prob and current-prob:
0.3 0.01
Do you have 'and' or 'or' branch :(yes/no)
no
Enter the number of arcs :
1
Enter the atoms name :
country-1
Please estimate the probability for calculating sufficiency and necessity :
0.01 0.001
Enter the current node name :
civilian-ship
Enter the prior-prob and current-prob:
0.6 0.85
Do you have 'and' or 'or' branch :(yes/no)
no
Enter the number of arcs :
3
Enter the atoms name :
country-1
Please estimate the probability for calculating sufficiency and necessity :
0.01 0.7
Enter the atoms name :
country-2
Please estimate the probability for calculating sufficiency and necessity :
0.85 0.001
Enter the atoms name :
country-3
Please estimate the probability for calculating sufficiency and necessity :
0.5 0.1
Enter the current node name :
aircraft
Enter the prior-prob and current-prob:
0.4 0.1
Do you have 'and' or 'or' branch :(yes/no)
no
Enter the number of arcs :
3
Enter the atoms name :
country-1
Please estimate the probability for calculating sufficiency and necessity :
0.01 0.7
Enter the atoms name :
country-2
Please estimate the probability for calculating sufficiency and necessity :
0.3 0.7
```

Enter the atoms name :
country-3
Please estimate the probability for calculating sufficiency and necessity :
0.001 0.8
Enter the current node name :
warship
Enter the prior-prob and current-prob:
0.7 0.85
Do you have 'and' or 'or' branch :(yes/no)
no
Enter the number of arcs :
3
Enter the atoms name :
country-1
Please estimate the probability for calculating sufficiency and necessity :
0.2 0.01
Enter the atoms name :
country-2
Please estimate the probability for calculating sufficiency and necessity :
0.7 0.001
Enter the atoms name :
country-3
Please estimate the probability for calculating sufficiency and necessity :
0.01 0.7

Enter the number of nodes in 4th level :
3
Enter the current node name :
nearest-point-land
Enter the prior-prob and current-prob:
0.6 0.01
Do you have 'and' or 'or' branch :(yes/no)
yes
Enter number of arcs except for 'and' or 'or' :
2
Enter the atoms name :
submarine
Please estimate the probability for calculating sufficiency and necessity :
0.001 0.7
Enter the atoms name :
aircraft
Please estimate the probability for calculating sufficiency and necessity :
0.1 0.6
Enter the number of 'and' or 'or' :
1
Enter 'and' or 'or' :
or
Enter the number of arcs :
2

Enter the atoms name :
civilian-ship
Please estimate the probability for calculating sufficiency and necessity :
0.7 0.3
Enter the atoms name :
warship
Please estimate the probability for calculating sufficiency and necessity :
0.8 0.1
Enter the current node name :
traffic-lane
Enter the prior-prob and current-prob:
0.7 0.9
Do you have 'and' or 'or' branch :(yes/no)
yes
Enter number of arcs except for 'and' or 'or' :
0
Enter the number of 'and' or 'or' :
1
Enter 'and' or 'or' :
or
Enter the number of arcs :
4
Enter the atoms name :
submarine
Please estimate the probability for calculating sufficiency and necessity :
0.5 0.01
Enter the atoms name :
civilian-ship
Please estimate the probability for calculating sufficiency and necessity :
0.8 0.1
Enter the atoms name :
aircraft
Please estimate the probability for calculating sufficiency and necessity :
0.5 0.1
Enter the atoms name :
warship
Please estimate the probability for calculating sufficiency and necessity :
0.8 0.001
Enter the current node name :
coast
Enter the prior-prob and current-prob:
0.7 0.4
Do you have 'and' or 'or' branch :(yes/no)
yes
Enter number of arcs except for 'and' or 'or' :
2
Enter the atoms name :
submarine
Please estimate the probability for calculating sufficiency and necessity :
0.4 0.1

Enter the atoms name :
aircraft
Please estimate the probability for calculating sufficiency and necessity :
0.3 0.7
Enter the number of 'and' or 'or' :
1
Enter 'and' or 'or' :
or
Enter the number of arcs :
2
Enter the atoms name :
civilian-ship
Please estimate the probability for calculating sufficiency and necessity :
0.85 0.1
Enter the atoms name :
warship
Please estimate the probability for calculating sufficiency and necessity :
0.85 0.01

Enter the number of nodes in 5th level :
2
Enter the current node name :
contact-mine
Enter the prior-prob and current-prob:
0.85 0.99
Do you have 'and' or 'or' branch :(yes/no)
yes
Enter number of arcs except for 'and' or 'or' :
1
Enter the atoms name :
traffic-lane
Please estimate the probability for calculating sufficiency and necessity :
0.85 0.01
Enter the number of 'and' or 'or' :
1
Enter 'and' or 'or' :
or
Enter the number of arcs :
2
Enter the atoms name :
nearest-point-land
Please estimate the probability for calculating sufficiency and necessity :
0.8 0.1
Enter the atoms name :
coast
Please estimate the probability for calculating sufficiency and necessity :
0.85 0.1
Enter the current node name :
induced-mine

```
Enter the prior-prob and current-prob:
0.6 0.7
Do you have 'and' or 'or' branch :(yes/no)
yes
Enter number of arcs except for 'and' or 'or' :
1
Enter the atoms name :
traffic-lane
Please estimate the probability for calculating sufficiency and necessity :
0.8 0.1
Enter the number of 'and' or 'or' :
1
Enter 'and' or 'or' :
or
Enter the number of arcs :
2
Enter the atoms name :
nearest-point-land
Please estimate the probability for calculating sufficiency and necessity :
0.01 0.7
Enter the atoms name :
coast
Please estimate the probability for calculating sufficiency and necessity :
0.7 0.1

Enter the number of nodes in 6th level :
1
Enter the current node name :
deploy-MCM-force
Enter the prior-prob and current-prob:
0.5 0.5
Do you have 'and' or 'or' branch :(yes/no)
yes
Enter number of arcs except for 'and' or 'or' :
0
Enter the number of 'and' or 'or' :
1
Enter 'and' or 'or' :
or
Enter the number of arcs :
2
Enter the atoms name :
contact-mine
Please estimate the probability for calculating sufficiency and necessity :
0.9 0.00001
Enter the atoms name :
induced-mine
Please estimate the probability for calculating sufficiency and necessity :
0.75 0.00001
GoodBye
```

APPENDIX C. DATA SEGMENT FOR LISP

```
; This data file, mcmdata.l, is created by the user.
; Each node is given by an expert. A complete node
; looks like:
;       (define-nede node-name prior-probability
;        current-probability arc-expression)
; The arc-expression consists of four cases:
;       (1). (),
;       (2). (indep
;             (arc: atom-name sufficiency necessity)
;             .....
;            ),
;       (3). (indep
;             (arc: atom-name sufficiency necessity)
;             .....
;             ('or' or 'and'
;              (arc: atom-name sufficiency necessity)
;              .....
;             )
;            ),
;       (4). (indep
;             ('or' or 'and'
;              (arc: atom-name sufficiency necessity)
;              .....
;             )
;            ).
; As we execute the main program in LISP, thesis.l,
; will call this data file to infer the probabilistic
; inference network.

(define-node mine-field 0.9000 0.5000 ())

(define-node country-1 0.7000 0.0010
 (indep
  (arc: mine-field 0.0125 4,9500)
 )
)

(define-node country-2 0.0100 0.8500
 (indep
  (arc: mine-field 850.0000 0.1502)
 )
)

(define-node country-3 0.3000 0.0100
 (indep
```

```
   (arc: mine-field 0.6250 2.5000)
  )
 )

 (define-node submarine 0.3000 0.0100
  (indep
   (arc: country-1 10.0000 0.9910)
  )
 )

 (define-node civilian-ship 0.6000 0.8500
  (indep
   (arc: country-1 0.0143 3.3000)
   (arc: country-2 850.0000 0.1502)
   (arc: country-3 5.0000 0.5556)
  )
 )

 (define-node aircraft 0.4000 0.1000
  (indep
   (arc: country-1 0.0143 3.3000)
   (arc: country-2 0.4286 2.3333)
   (arc: country-3 0.0013 4.9950)
  )
 )

 (define-node warship 0.7000 0.8500
  (indep
   (arc: country-1 20.0000 0.8081)
   (arc: country-2 699.9999 0.3003)
   (arc: country-3 0.0143 3.3000)
  )
 )

 (define-node nearest-point-land 0.6000 0.0100
  (indep
   (arc: submarine 0.0014 3.3300)
   (arc: aircraft 0.1667 2.2500)
   (or
    (arc: civilian-ship 2.3333 0.4286)
    (arc: warship 8.0000 0.2222)
   )
  )
 )

 (define-node traffic-lane 0.7000 0.9000
  (indep
   (or
    (arc: submarine 50.0000 0.5051)
    (arc: civilian-ship 8.0000 0.2222)
```

```
    (arc: aircraft 5.0000 0.5556)
    (arc: warship 800.0000 0.2002)
   )
  )
 )

(define-node coast 0.7000 0.4000
 (indep
  (arc: submarine 4.0000 0.6667)
  (arc: aircraft 0.4286 2.3333)
  (or
  (arc: civilian-ship 8.5000 0.1667)
  (arc: warship 85.0000 0.1515)
  )
 )
)

(define-node contact-mine 0.8500 0.9900
 (indep
  (arc: traffic-lane 85.0000 0.1515)
  (or
   (arc: nearest-point-land 8.0000 0.2222)
   (arc: coast 8.5000 0.1667)
  )
 )
)

(define-node induced-mine 0.6000 0.7000
 (indep
  (arc: traffic-lane 8.0000 0.2222)
  (or
   (arc: nearest-point-land 0.0143 3.3000)
   (arc: coast 7.0000 0.3333)
  )
 )
)

(define-node deploy-MCM-force 0.5000 0.5000
 (indep
  (or
   (arc: contact-mine 90000.0000 0.1000)
   (arc: induced-mine 75000.0000 0.2500)
  )
 )
)

(defun test() (update-nodes '( country-1 country-2 country-3
 submarine civilian-ship aircraft warship nearest-point-land
 traffic-lane coast contact-mine induced-mine deploy-MCM-force )))
```

APPENDIX D. SIMULATION RESULTS

inhibitive probability updating for node country-1 along arc:
(mine-field 0.0125 4.95) with prior odds 2.333333333333333.
Prior and current probs of evident are 0.9 and 0.5.
Current probability of node country-1 is 0.7979194333776007.

inhibitive probability updating for node country-2 along arc:
(mine-field 850.0 0.1502) with prior odds 0.0101010101010101.
Prior and current probs of evident are 0.9 and 0.5.
Current probability of node country-2 is 0.006228832619601373.

inhibitive probability updating for node country-3 along arc:
(mine-field 0.625 2.5) with prior odds 0.4285714285714286.
Prior and current probs of evident are 0.9 and 0.5.
Current probability of node country-3 is 0.396551724137931.

supportive probability updating for node submarine along arc:
(country-1 10.0 0.991) with prior odds 0.4285714285714286.
Prior and current probs of evident are 0.7 and 0.7979194333776007.
Current probability of node submarine is 0.466727683859158.

supportive probability updating for node civilian-ship along arc:
(country-1 0.0143 3.3) with prior odds 1.5.
Prior and current probs of evident are 0.7 and 0.7979194333776007.
inhibitive probability updating for node civilian-ship along arc:
(country-2 850.0 0.1502) with prior odds 1.5.
Prior and current probs of evident are 0.01 and 0.006228832619601373.
supportive probability updating for node civilian-ship along arc:
(country-3 5.0 0.5556) with prior odds 1.5.
Prior and current probs of evident are 0.3 and 0.396551724137931.
Current probability of node civilian-ship is 0.303937851020989.

supportive probability updating for node aircraft along arc:
(country-1 0.0143 3.3) with prior odds 0.6666666666666667.
Prior and current probs of evident are 0.7 and 0.7979194333776007.
inhibitive probability updating for node aircraft along arc:
(country-2 0.4286 2.3333) with prior odds 0.6666666666666667.
Prior and current probs of evident are 0.01 and 0.006228832619601373.
supportive probability updating for node aircraft along arc:
(country-3 0.0013 4.995) with prior odds 0.6666666666666667.
Prior and current probs of evident are 0.3 and 0.396551724137931.
Current probability of node aircraft is 0.2895644212476534.

supportive probability updating for node warship along arc:
(country-1 20.0 0.8081) with prior odds 2.333333333333333.
Prior and current probs of evident are 0.7 and 0.7979194333776007.

inhibitive probability updating for node warship along arc:
(country-2 699.9999 0.3003) with prior odds 2.333333333333333.
Prior and current probs of evident are 0.01 and 0.006228832619601373.
supportive probability updating for node warship along arc:
(country-3 0.0143 3.3) with prior odds 2.333333333333333.
Prior and current probs of evident are 0.3 and 0.396551724137931.
Current probability of node warship is 0.6094573045137574.

supportive probability updating for node nearest-point-land along arc:
(submarine 0.0014 3.33) with prior odds 1.5.
Prior and current probs of evident are 0.3 and 0.4667276683859158.
inhibitive probability updating for node nearest-point-land along arc:
(aircraft 0.1667 2.25) with prior odds 1.5.
Prior and current probs of evident are 0.4 and 0.2895644212476534.
inhibitive probability updating for node nearest-point-land along arc:
(civilian-ship 2.3333 0.4286) with prior odds 1.5.
Prior and current probs of evident are 0.6 and 0.303937851020989.
inhibitive probability updating for node nearest-point-land along arc:
(warship 8.0 0.2222) with prior odds 1.5.
Prior and current probs of evident are 0.7 and 0.6094573045137574.
Current probability of node nearest-point-land is 0.46160740726002.

supportive probability updating for node traffic-lane along arc:
(submarine 50.0 0.5051) with prior odds 2.333333333333333.
Prior and current probs of evident are 0.3 and 0.4667276683859158.
inhibitive probability updating for node traffic-lane along arc:
(civilian-ship 8.0 0.2222) with prior odds 2.333333333333333.
Prior and current probs of evident are 0.6 and 0.303937851020989.
inhibitive probability updating for node traffic-lane along arc:
(aircraft 5.0 0.5556) with prior odds 2.333333333333333.
Prior and current probs of evident are 0.4 and 0.2895644212476534.
inhibitive probability updating for node traffic-lane along arc:
(warship 800.0 0.2002) with prior odds 2.333333333333333.
Prior and current probs of evident are 0.7 and 0.6094573045137574.
Current probability of node traffic-lane is 0.76943050857591.

supportive probability updating for node coast along arc:
(submarine 4.0 0.6667) with prior odds 2.333333333333333.
Prior and current probs of evident are 0.3 and 0.4667276683859158.
inhibitive probability updating for node coast along arc:
(aircraft 0.4286 2.3333) with prior odds 2.333333333333333.
Prior and current probs of evident are 0.4 and 0.2895644212476534.
inhibitive probability updating for node coast along arc:
(civilian-ship 8.5 0.1667) with prior odds 2.333333333333333.
Prior and current probs of evident are 0.6 and 0.303937851020989.
inhibitive probability updating for node coast along arc:
(warship 85.0 0.1515) with prior odds 2.333333333333333.
Prior and current probs of evident are 0.7 and 0.6094573045137574.
Current probability of node coast is 0.73708420559377.

supportive probability updating for node contact-mine along arc:
(traffic-lane 85.0 0.1515) with prior odds 5.666666666666667.
Prior and current probs of evident are 0.7 and 0.76943050857591.
inhibitive probability updating for node contact-mine along arc:
(nearest-point-land 8.0 0.2222) with prior odds 5.666666666666667.
Prior and current probs of evident are 0.6 and 0.46160740726002.
supportive probability updating for node contact-mine along arc:
(coast 8.5 0.1667) with prior odds 5.666666666666667.
Prior and current probs of evident are 0.7 and 0.73708420559377.
Current probability of node contact-mine is 0.8970485714594268.

supportive probability updating for node induced-mine along arc:
(traffic-lane 8.0 0.2222) with prior odds 1.5.
Prior and current probs of evident are 0.7 and 0.76943050857591.
inhibitive probability updating for node induced-mine along arc:
(nearest-point-land 0.0143 3.3) with prior odds 1.5.
Prior and current probs of evident are 0.6 and 0.46160740726002.
supportive probability updating for node induced-mine along arc:
(coast 7.0 0.3333) with prior odds 1.5.
Prior and current probs of evident are 0.7 and 0.73708420559377.
Current probability of node induced-mine is 0.7228861921773642.

supportive probability updating for node deploy-MCM-force along arc:
(contact-mine 90000.0 0.1) with prior odds 1.0.
Prior and current probs of evident are 0.85 and 0.8970485714594268.
supportive probability updating for node deploy-MCM-force along arc:
(induced-mine 75000.0 0.25) with prior odds 1.0.
Prior and current probs of evident are 0.6 and 0.7228861921773642.
Current probability of node deploy-MCM-force is 0.6568250864907779.
nil

APPENDIX E. CERTAINTY FACTORS CONCLUSIONS

The following explanations are starting from top to bottom in Table 4-1.

H = The country-1 will lay the mines;
E = The mine-field is existence;
CF[H,E] = –0.9693 : There is weakly suggestive evidence (0.9693) that the country-1 will lay the mines.

H = The country-2 will lay the mines;
E = The mine-field is existence;
CF[H,E] = 0.8946 : There is strongly suggestive evidence (0.8946) that the country-2 will lay the mines.

H = The country-3 will lay the mines;
E = The mine-field is existence;
CF[H,E] = –0.2958 : There is not weakly suggestive evidence (0.2958) that the country-3 will lay the mines.

H = The submarine will deliver the mines;
E = The country-1 will use it;
CF[H,E] = 0.7297 : There is strongly suggestive evidence (0.7297) that the submarine will deliver the mines.

H = The civilian-ship will deliver the mines;
E = The country-1 will use it;
CF[H,E] = –0.9650 : There is weakly suggestive evidence (0.9650) that the civilian-ship will deliver the mines.

H = The civilian-ship will deliver the mines;
E = The country-2 will use it;
CF[H,E] = 0.9980 : There is strongly suggestive evidence (0.9980) that the civilian-ship will deliver the mines.

H = The civilian-ship will deliver the mines;
E = The country-3 will use it;
CF[H,E] = 0.7059 : There is strongly suggestive evidence (0.7059) that the civilian-ship will deliver the mines.

H = The aircraft will deliver the mines;
E = The country-1 will use it;
CF[H,E] = –0.9764 : There is weakly suggestive evidence (0.9764) that the aircraft will deliver the mines.

H = The aircraft will deliver the mines;
E = The country-2 will use it;
CF[H,E] = –0.4444 : There is not weakly suggestive evidence (0.4444) that the aircraft will deliver the mines.

H = The aircraft will deliver the mines;
E = The country-3 will use it;
CF[H,E] = –0.9979 : There is weakly suggestive evidence (0.9979) that the aircraft will deliver the mines.

H = The warship will deliver the mines;
E = The country-1 will use it;
CF[H,E] = 0.9301 : There is strongly suggestive evidence (0.9301) that the warship will deliver the mines.

H = The warship will deliver the mines;
E = The country-2 will use it;
CF[H,E] = 0.9980 : There is strongly suggestive evidence (0.9980) that the warship will deliver the mines.

H = The warship will deliver the mines;
E = The country-3 will use it;
CF[H,E] = –0.9540 : There is weakly suggestive evidence (0.9540) that the warship will deliver the mines.

H = The mines will lay at the nearest-point-land;
E = The submarine will do it;
CF[H,E] = –0.9964 : There is weakly suggestive evidence (0.9964) that the mines will lay at the nearest-point-land.

H = The mines will lay at the nearest-point-land;
E = The aircraft will do it;
CF[H,E] = –0.6667 : There is weakly suggestive evidence (0.6667) that the mines will lay at the nearest-point-land.

H = The mines will lay at the nearest-point-land;
E1 = The civilian-ship will do it; OR
E2 = The warship will do it;
CF[H,E1VE2] = 0.8077 : There is strongly suggestive evidence (0.8077) that the mines will lay at the nearest-point-land.

H = The mines will lay at the traffic-lane;
E1 = The submarine will do it; OR
E2 = The civilian-ship will do it; OR
E3 = The warship will do it; OR

E4 = The aircraft will do it;
CF[H,E] = 0.9982 : There is strongly suggestive evidence (0.9982) that the mines will lay at the traffic-lane.

H = The mines will lay at the coast;
E = The submarine will do it;
CF[H,E] = 0.6774 : There is strongly suggestive evidence (0.6774) that the mines will lay at the coast.

H = The mines will lay at the coast;
E = The aircraft will do it;
CF[H,E] = −0.2857 : There is not weakly suggestive evidence (0.2857) that the mines will lay at the coast.

H = The mines will lay at the coast;
E1 = The civilian-ship will do it; OR
E2 = The warship will do it;
CF[H,E1VE2] = 0.9833 : There is strongly suggestive evidence (0.9833) that the mines will lay at the coast.

H = The contact-mine will be laid;
E = The mines will lay at the traffic-lane;
CF[H,E] = 0.9862 : There is strongly suggestive evidence (0.9862) that the contact-mine will be laid.

H = The contact-mine will be laid;
E1 = The mines will lay at the nearest-point-land; OR
E2 = The mines will lay at the coast;
CF[H,E] = 0.8644 : There is strongly suggestive evidence (0.8644) that the contact-mine will be laid.

H = The induced-mine will be laid;
E = The mines will lay at the traffic-lane;
CF[H,E] = 0.8077 : There is strongly suggestive evidence (0.8077) that the induced-mine will be laid.

H = The induced-mine will be laid;
E1 = The mines will lay at the nearest-point-land; OR
E2 = The mines will lay at the coast;
CF[H,E] = 0.7825 : There is strongly suggestive evidence (0.7825) that the induced-mine will be laid.

H = To deploy the MCM force;
E1 = The contact-mine will be laid; OR
E2 = The induced-mine will be laid;

CF[H,F] = 1.0 : There is definite (1.0) that to deploy the MCM force.

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