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SYSTEMS INTEGRATION STUDY OF A HIERARCHICAL MINEFIELD IMAGE ANALYSIS ALGORITHM REPORT TO END OF PHASE 2 (U)

BY

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DECEMBER 1994

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SYSTEMS INTEGRATION STUDY OF A HIERARCHICAL MINEFIELD IMAGE ANALYSIS ALGORITHM

REPORT TO END OF PHASE 2

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August 4, 1994

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Abstract

The Threat Detection Group at the Defence Research Establishment Suffield has undertaken a research program on the feasibility of the remote sensing of minefields. A contract exists to investigate the use of an image processing system in minefield detection by testing various algorithms and measuring their effectiveness.

The prime focus of the report is placed on the investigation of the high level of the Remote Minefield Detection hierarchical algorithm, target spatial analysis. The study involves identifying suitable pattern recognition techniques and selecting appropriate system architecture, expert system and transputer network, for the task. In the construction of the expert system, scope of the knowledge base is introduced and a testing methodology to evaluate the performance of both the expert system and knowledge base is proposed.

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1. Glossary

Backward chaining A goal-directed searching strategy which starts at the end solution and works backward towards the initial conditions. It is known as top-down processing.
Best-first A heuristic search technique based on the selection of the next best open node, no matter where it is located on the tree.
Expert reports A knowledge acquisition technique where data, rules and strategies for the solution are prepared by the knowledge engineer.
Forward chaining (data-driven) A searching strategy starting with initial given data or knowledge and searching forward through the knowledge base towards a solution. It is known as bottom-up processing.
Frames A knowledge representation consisting of a collection of slots which contain attributes to describe an object, a situation, an event or an action.
(GRC) Global Region Classification The stage in the high level of the Remote Minefield Detection hierarchical algorithm that assigns the feature vectors to their most likely group.
(GRFE) Global Region Feature Extraction The stage in the high level of the Remote Minefield Detection hierarchical algorithm in which various morphological features such as pixel area, average pixel intensity and region compactness are measured for image regions.
Hill-Climbing A heuristic search technique based on an estimation of the closeness to the target. If a particular search were unsuccessful, a path that was declined earlier would be reevaluated using additional rules to approximate the closeness to the goal before attempting a new path not yet evaluated.
(LRC) Local Region Classification The stage in the Remote Minefield Detection hierarchical algorithm that assigns the feature vectors to their most likely group.
(LRFE) Local Region Feature Extraction The stage in the Remote Minefield Detection hierarchical algorithm in which various morphological features such as pixel area, average pixel intensity and region compactness are measured for image regions.
Production rule A condition/action rule. In general it obtains the form of *If-then.*
(RMD) Remote Minefield Detection The process of detecting minefields from an airborne platform. Also called Standoff Minefield Detection.
Rule-Based An expert system structure whereby the knowledge base is entered into the system through production rules.

(TSA) Target Spatial Analysis The stage in the Remote Minefield Detection hierarchical algorithm which attempts to describe and interpret the relative positions of suspect mines.

2. Introduction

The Threat Detection Group at the Defence Research Establishment Suffield has undertaken a research program on the feasibility of remote sensing of scatterable and patterned minefields (commonly called remote minefield detection or RMD). Under the contract (DSS W7702-6-2795), the framework of the RMD hierarchical image analysis algorithm for active infrared imagery was developed. Also, in the second contract (DSS W7702-9-R121), the study of the system hardware consisting of an array of vector processors and a transputer network designed for each individual stage of the low and middle levels of the RMD hierarchical algorithm [1] was initiated. Under the current contract (DSS W7702-1-R286), the study of the systems integration of both hardware and software aspects of the low and middle levels of the RMD hierarchy has been completed in the first phase.

The primary goal of the second phase is to investigate the high level, Target Spatial Analysis (TSA), of the RMD hierarchy. The report consists of two parts.

In the first part the report presents two types of minefield patterns: scatterable and patterned. It then introduces two pattern recognition techniques, statistical and syntactic, which are used to identify the patterns. A set of features for the statistical recognition and rules for the syntactic recognition are proposed. The report also discusses the selection of the best approach for implementing syntactic pattern recognition.

The second part of the report introduces requirements for an expert system. Nexpert object is selected for the system shell. A general scope of the knowledge base is presented, and a testing methodology to evaluate the performance of the expert system and knowledge base is suggested.

3. Target Spatial Analysis

Target Spatial Analysis (TSA) is the high level of the RMD hierarchy. At this level the spatial relationship of the XY coordinates of the mine-like objects, discovered at the low level, is examined. Two statistically-based modules, Global Region Feature Extraction (GRFE) and Global Region Classification (GRC), are initiated to identify minefield patterns. GRFE requires not only statistical but also syntactic pattern recognition approaches to identify the patterns.

3.1 Types of minefield

In a battle field, threat forces generally prepare 2 types of minefield, deliberate and hasty. When the offence has temporarily stalled, deliberate minefield employment is used. Hasty minefield employment can be expected in a number of circumstances; for instance a case in which minimum force is used to protect the flank of a breakthrough against a counterattack.

In emplacing deliberate minefields, threat forces employ multiple techniques. Mines can be mechanically buried by dispensing systems or laid by hand into defined regular patterns.

In the establishment of a hasty minefield, mines are often delivered by air using various methods, such as artillery, helicopters or jet aircraft. Normally only in a very short time (within minutes) a highly mobile and especially prepared and equipped combat engineer unit must be ready to rapidly scatter mines over specified zones.

In summary there are two basic types of minefields: patterned and scatterable as depicted in the following figures.

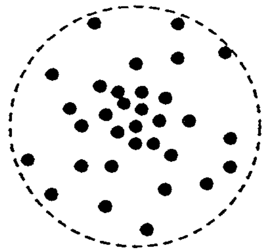

Figure 3.1: Scatterable circular minefield.

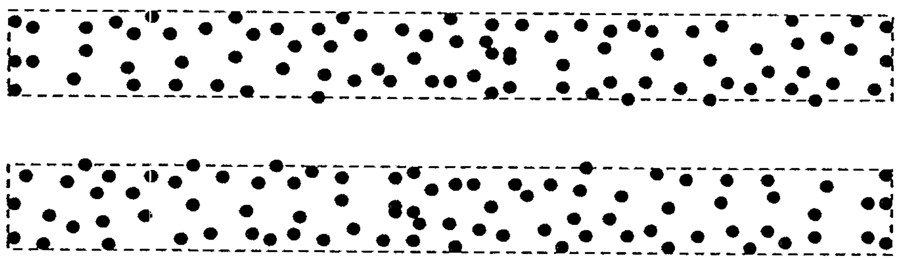

Figure 3.2: Scatterable row minefield.

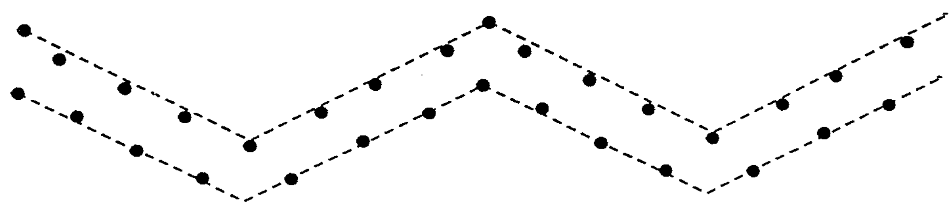

Figure 3.3: Patterned zigzag minefield.

3.2 Statistical pattern recognition

Statistical pattern recognition is a method which provides the proper framework for classifying targets when the system-generating mechanism can be represented by a statistical model. The goal of statistical pattern recognition is to determine whether or not a given pattern belongs to some preclassified set of patterns.

When mines are dropped from the air by artillery or helicopter, they tend to scatter on the ground. Because mines are distributed randomly it is appropriate to choose a statistical pattern recognition approach in pursuit of the solution of minefield pattern detection problem.

The mathematical definition of the features is given as follows: $\mathcal{F}_j^l$ is the l^{th} feature of the j^{th} region, $D_j(x_i, y_i, x_k, y_k) = \sqrt{(x_i - x_k)^2 + (y_i - y_k)^2}$ is the distance between point(x_i, y_i) and point(x_k, y_k) in the j^{th} region.

1. Total number of mines.

$$\mathcal{F}_j^1 = \sum_{(x,y)\in j} 1$$

2. Intra-distance mean – average distance between points of region j

$$\mathcal{F}_j^2 = \frac{2}{\mathcal{F}_j^1(\mathcal{F}_j^1 - 1)} \sum_{i=0}^{(\mathcal{F}_j^1-1)} \sum_{k=i}^{\mathcal{F}_j^1} D_j(x_i, y_i, x_k, y_k)$$

3. Intra-distance variance.

$$\mathcal{F}_j^3 = \frac{2}{\mathcal{F}_j^1(\mathcal{F}_j^1 - 1)} \sum_{i=1}^{(\mathcal{F}_j^1-1)} \sum_{k=i}^{\mathcal{F}_j^1} \left(D_j(x_i, y_i, x_k, y_k) - \mathcal{F}_j^2\right)^2$$

4. Maximum Intra-distance.

$$\mathcal{F}_j^4 = max_{i,k}\left(D_j(x_i, y_i, x_k, y_k)\right)$$

5. Minimum Intra-distance.

$$\mathcal{F}_j^5 = min_{i,k}\left(D_j(x_i, y_i, x_k, y_k)\right)$$

6. Density$\left(\frac{mines}{m^2}\right)$

$$\mathcal{F}_j^6 = \frac{1}{\pi\left(\frac{\mathcal{F}_j^2}{2}\right)^2}$$

7. 1st, 2nd and 3rd central moments of region j.

$$\mathcal{F}_j^7 = \sum_{(x_i,y_i)\in j} (x_i - \mathcal{X}_j)(y_i - \mathcal{Y}_j)$$

$$\mathcal{F}_j^8 = \sum_{(x_i,y_i)\in j} (x_i - \mathcal{X}_j)^2(y_i - \mathcal{Y}_j)^2$$

$$\mathcal{F}_j^9 = \sum_{(x_i,y_i)\in j} (x_i - \mathcal{X}_j)^3(y_i - \mathcal{Y}_j)^3$$

where $\mathcal{X}_j = \frac{1}{\mathcal{F}_j^1}\sum_{(x_i,y_i)\in j} x_i$ and $\mathcal{Y}_j = \frac{1}{\mathcal{F}_j^1}\sum_{(x_i,y_i)\in j} y_i$ are the coordinates of the center of gravity of region j .

8. Total number of clusters.

$$\mathcal{F}^{10} = \sum_i 1, \qquad \text{each } i \text{ is a region and} \qquad i = 1, 2, \ldots$$

9. Inter-distance mean – distance between centers of gravity of clusters. (x_i, y_i) and (x_j, y_j) are the centers of gravity of region i and j respectively.

$$\mathcal{F}^{11} = \frac{2}{\mathcal{F}^{10}(\mathcal{F}^{10} - 1)} \sum_{i=1}^{\mathcal{F}^{10}-1} \sum_{j=i}^{\mathcal{F}^{10}} \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$$

3.3 Syntactic pattern recognition

Syntactic pattern recognition is a technique which explicitly utilizes the structure of patterns in the recognition process.

When deliberate minefields are deployed in battle field situations, they tend to conform to 2 basic shapes, straight and zigzag. However the number of possible descriptions is very large, especially the zigzag, because the shape varies greatly with length and apex angles (figures 3.4). It is impractical to consider each description as defining a class. Thus to solve the problem, syntactic pattern recognition is selected.

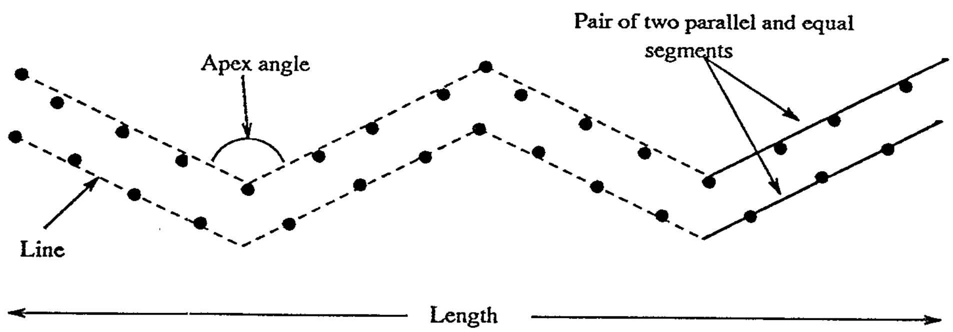

Figure 3.4: Display of a typical patterned zigzag minefield.

The following is a proposed structural representation of patterned minefields which can be used to recognize the patterns.

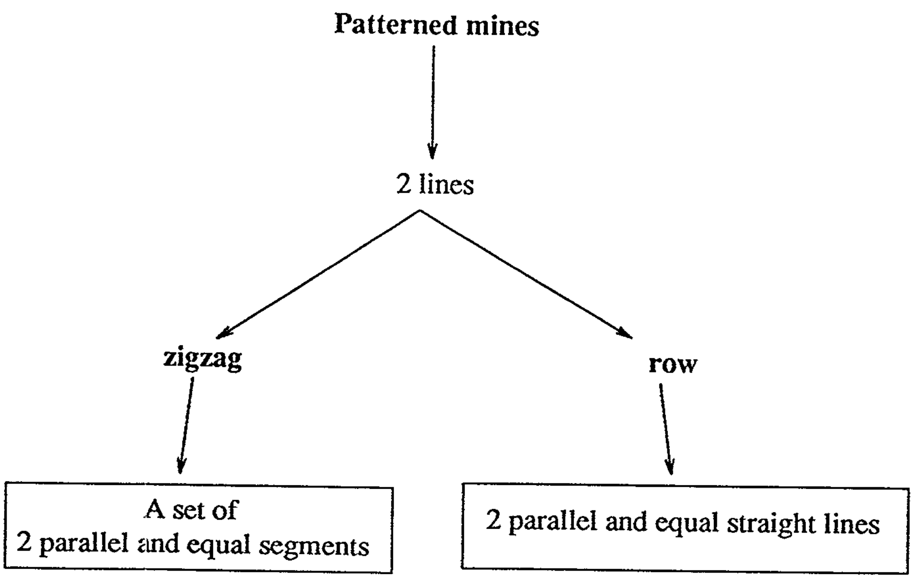

Figure 3.5: Hierarchical structure representation of patterned minefield.

The algorithm to detect patterned mines is

```
IF (Exist 2 lines) {
      IF (Exist 2 parallel and equal straight lines) ⇒ patterned row mines
      IF (Exist a set of 2 parallel and equal segments) ⇒ patterned zigzag mines
}
```

3.4 Method for implementing syntactic pattern recognition

For simple patterns it is not difficult to devise an algorithm to recognize the patterns, but when the patterns become more complex the algorithm can get more complicated and time consuming. In other words, it is not recommended to use conventional programs to implement syntactic pattern recognition for complicated patterns.

It is noted that syntactic pattern recognition is an if-then based decision process, the type of reasoning process that an expert system excels on. Therefore it is best to implement the algorithm on the expert system which is available after the TSA stage.

After being extracted in the TSA stage, syntactic features are passed on to the expert system for processing. Thus in the expert system besides the module developed for recognition of the whole minefield, a small module for the syntactic pattern recognition is to be implemented at front.

3.5 Computing architecture for GRFE and GRC

Similar to LRFE and LRC in the middle stage, GRFE is built to extract features both statistical and syntactic, and GRC is constructed for the classification of patterns.

Because the data rate to the upper stage (TSA) of the RMD hierarchy (about 2×1280 B/s in the worst case) much smaller than the rate to the middle stage (64 KB/s), it can be concluded that GRFE needs 1 T800 transputer, and GRC requires 4 T800s connected in a ring network, based on the number of transputers estimated for LRFE and LRC presented in [8].

4. Introduction of an expert system

An expert system is a computer system, consisting of software and hardware that attempts to mimic an expert's thought processes to solve complex problems or make decisions in a given field.

An expert system operates on a processing level higher than that of conventional programs. It uses not only the conventional mathematical and Boolean operators (e.g +,-,AND ...), but also human reasoning processes such as "rule of thumb" and "shortcuts" to solve problems. It has the capability of manipulating vast amounts of information and integrating relevant pieces of data from a knowledge base using reasoning techniques, commonly known as heuristics, to emulate the expert. The top level of the RMD hierarchical algorithm involves the integration of disparate types of knowledge, including conflict resolution. The characteristics of an expert system make it ideally suited for this task.

An expert system is composed of 4 basic components:

1. The knowledge base: including the related and unrelated relationships of the data of the problem.
2. The working memory: responsible for combining data from the database, knowledge from the knowledge base, and input information from the user, and then transporting them to the inference engine.
3. The inference engine: the "thinker" of a problem solving system, consisting of established reasoning and search strategies. It takes the information gathered by the working memory and then massages them to pursue a solution.
4. The development engine: knowledge acquisition subsystem, allowing the knowledge engineers to add, delete, modify and create information in the knowledge base.

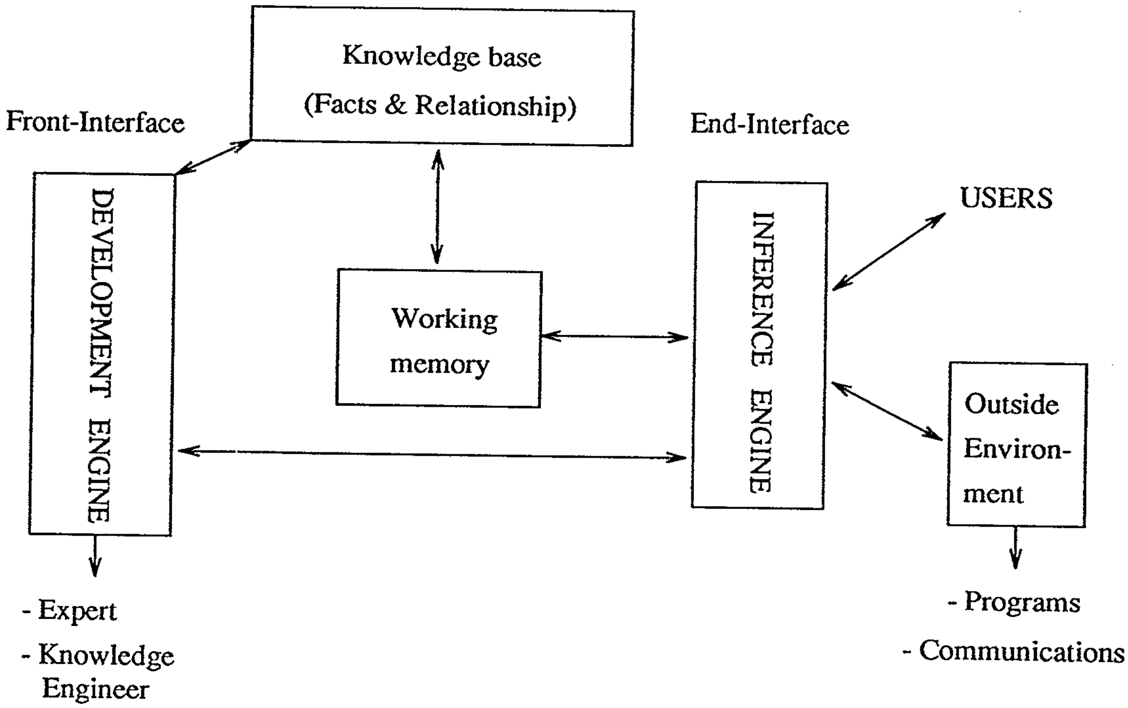

Figure 4.1: Basic components of an expert system.

4.1 Expert system Shell

A suitable commercial system shell, *Nexpert Object*, has been chosen for the task, and the shell has the following significant features:

- Knowledge representation model: production rules (ruled-base).
- Problem solving strategy: Forward chaining or backward chaining which can be switched on and off by choice, or a combination of forward and backward chaining by default.
- Friendly user interface.

4.2 Scope of the knowledge base

The knowledge base of an expert system is the collection of information which can be extracted by the expert system in pursuit of a solution for a problem. The significant feature of the knowledge base is that the knowledge base contains not only static data as in database but also relational information.

For the RMD knowledge base, the knowledge representation model is a set of production rules. Forward chaining is the problem solving strategy. Expert report technique is suggested for the acquisition of information during processing.

The static database consists of information derived from:

1. Physical geography of the area:

   - Types of terrain: rocks, marshes, swamps, bogs, flat uplands, river, desert ...
   - Types of vegetation: tree, shrub, herb, moss .. and the range (height).
   - Texture of terrain: coarse, fine, medium, ultrafine.

2. Tactical Command Control and Communication System (TCCCS) (A distributed processing computer network system which consists of a large number of cells deployed throughout the corps area.)

   - Types of mine delivery means available from enemy forces: hand, mechanical dispenser, helicopter, artillery ...
   - Enemy's tactics such as supporting both offensive maneuver (flank minefields) and the defense.
   - Types and availability of mines from enemy forces: anti-tank wooden mines, anti-personnel mines: pmn6, butterfly, ...
   - Positions of enemy's tactical group and weapons (armor, artillery), and the method of deployment to cover the minefield.
   - The threat from enemy air attack.
   - The ability of the enemy's detection and command, control and communications systems to execute an effective minefield deployment.
   - Location states of all friendly forces in the vicinity.

In addition, the database includes site specific information supplied from the battle field personnel or head quarters command level which can be added to or written over the knowledge base before or during processing.

Relational information includes production rules: If-then or If-then-else

4.3 Testing methodology

Testing how well the expert system and the knowledge base perform is very crucial at this stage. The evaluation can be done by executing several test scenarios that the knowledge engineer (expert) has already solved to see if the expert system generates the same answers through the same reasoning process.

The evaluation can be subdivided into 2 areas, static and dynamic.

1. The *static evaluation* is the testing of the knowledge base for its consistency and completeness. To test the completeness we should constantly ask ourselves, throughout the evaluation process, does more knowledge need to be added to produce the correct answers.

2. The *dynamic evaluation* is the testing of the reasoning process and the advice given. The accuracy and the reliability of the decision is crucial. The important part of the dynamic evaluation is asking for an audit trail of a decision and comparing it against an expert's reasoning.

5. Conclusion

At the completion of the second phase of the contract it was concluded that both statistical and syntactic pattern recognition approaches must be run in parallel to produce sufficient information for the pattern recognition process executed by the expert system. Two modules, GRFE and GRC, were introduced at the TSA stage. Both the GRFE and GRC algorithms can be implemented on a transputer network. One T800 transputer is needed for GRFE and four T800s for GRC using a ring configuration. The classification portion of the syntactic pattern recognition problem is best solved by an expert system.

In the construction of the expert system, an expert system shell called Nexpert object has been selected. Information needed to be included in the knowledge base was presented in Section 4.1 and a test methodology was proposed in Section 4.3.

As we progressed in the work of Phase 2, it was found that more work was needed to be done at the top level of the hierarchy than had been envisioned. Especially, more effort was directed to the statistical analysis of the target clusters (GRFE and GRC) and the syntactic analysis. In addition, during Phase 2, we unexpectedly managed to obtain real minefield images to supplement our simulated ones. Because the documentation for the images was sketchy, this necessitated a redirection of our effort in searching for an appropriate method to read the images, format them in a fashion compatible with our computing system, modify the current implementation of the algorithm to accept the images and test the algorithm on them. It was important to test the algorithm on these images at this stage, since some algorithm parameters were adjusted on the basis of performance on available images; these parameters are important in the later system integration. In summary, in Phase 2, the last item of the statement of work, involving constructing a data interface between the middle level of the hierarchy and the expert system, has not been completed.

The future work will include defining the data interface between the middle level of the hierarchy and the expert system. The middle level modules, through a supervisor, will provide input to the expert system. The input will consist of locations of mine-like objects, the probability that each object is consistent with being a mine and the type and nature (i.e., texture, etc.) of the background material on which the objects are situated. To minimize computation by the expert system, the previous information may be transformed into a form more suitable for an expert system, such as object densities, connectivity, pattern descriptors, etc. The expert system will be responsible for assessing the information, together with a body of knowledge related to typical scenarios for minefield laying, up-to-date military tactical strategies, on-the-spot information (such as known troop positions) and override instructions on certain aspects of the reasoning. Its output will be the probability that the area under study is a minefield and, if requested, the reasoning that led to the decision.

Also, additional artificial images will be generated for later testing and some preliminary testing will be conducted on real minefield data.

Appendix A
RMD nonparametric clustering algorithm

A number of early cluster-seeking algorithms were introduced and used extensively, such as the K-Means or ISODATA algorithm [4], or the fuzzy techniques by Ruspini [2], subsequently modified by Bezdek [6], Gath and Geva [5] and Rose *et al.* [7]. However, these algorithms suffer three major difficulties:

1. High sensitivity to the initialization of cluster centers.
2. Poor performance if the data contain overlapping clusters.
3. Inability to handle clusters with variability in size, density and shape.

In 1974 F. M. Fromm introduced a nonparametric clustering algorithm (CLASS) [3], and in 1993 Y. Wong invented a Melting algorithm [9]. They quite successfully overcome the first difficulty (cluster center initialization). Still, they both suffer the last two.

In our particular RMD problem, at the beginning of the GRC stage, there exists a clustering problem which is not only sensitive to cluster initialization but also contains overlapping clusters which vary with size, density and shape. Thus to resolve these problems a new algorithm, called RMD nonparametric clustering, has been introduced.

The algorithm, at first, adopts the techniques of cluster initialization from the CLASS and Melting algorithms to initialize clusters. It then uses a procedure, called Split, to examine the early found clusters to see if they can be separated into subclusters. The procedure stops when no more splitting occurs. The Split procedure decides to break a cluster when a "local valley" density is found. "Local valley" density is a value $(=\frac{mines}{meter^2})$ which is smaller than the ones of the adjacent areas. Finally, the algorithm executes a procedure, named Merge, to test if one cluster can be merged to the others. Once again, the "local valley" density concept is used, and in this case, two clusters are combined only if there exists no local valley density between them.

It is noted that two values of minefield density, .003 and .01 $\frac{mines}{meter^2}$ [10], are used to form an upper and a lower bound so that the number of loops required in the process searching for clusters is reduced.

To begin presenting the algorithm, let us denote N_c the number of cluster centers Z_i with $i = 1, 2, ..N_c$, and S a set of N samples: $\mathbf{X_1}, \mathbf{X_2}, ..., \mathbf{X_N}$ where $\mathbf{X_i}=(x_i, y_i)$ for all $\mathbf{i}$. The algorithm consists of the following steps:

1. Initialize a set of 5 cluster centers $\{\mathbf{Z_1}, \mathbf{Z_2}, \mathbf{Z_3}, \mathbf{Z_4}, \mathbf{Z_5}\} = \{(\overline{x} + S_x, \overline{y} + S_y), (\overline{x} + S_x, \overline{y} - S_y), (\overline{x} - S_x, \overline{y} + S_y), (\overline{x} - S_x, \overline{y} - S_y), (\overline{x}, \overline{y})\}$, where:

$$\overline{x} = \frac{1}{N} \sum_{i=1}^{N} x_i$$

$$\overline{y} = \frac{1}{N} \sum_{i=1}^{N} y_i$$

$$S_x = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} (x_i - \overline{x})^2}$$

$$S_y = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} (y_i - \overline{y})^2}$$

   for $\forall (x_i, y_i) \in S$

2. Apply nearest neighbor criterion to all samples: $\mathbf{X_k}$, k =1,2,...,N in S using the relation:

$$\textbf{If} \ \ \| \mathbf{X_k} - \mathbf{Z_j} \| < \| \mathbf{X_k} - \mathbf{Z_i} \|; \quad \forall \mathbf{X_k} \in S; \ i = 1, 2, ..., N_c; \ i \neq j$$

$$\textbf{Then } \mathbf{X_k} \in S_j$$

   where S_j is a cluster or a subset of S and assigned to center $\mathbf{Z_j}$.

3. Recompute each cluster center $\mathbf{Z_j}$, $j = 1, 2, ..., N_c$, by setting it equal to the sample mean of its corresponding set S_j.

$$\mathbf{Z_j} = \frac{1}{N_j} \sum_{\mathbf{X} \in S_j} \mathbf{X}$$

   where N_j is the number of samples in S_j.

4. Determine if the cluster S_j, centered at $\mathbf{Z_j}$ with $j = 1, 2, ..., N_j$, is to be split into two.

   (a) Compute the intra-distance mean (idm_j).

$$idm_j = \frac{2}{N_j^1(N_j^1 - 1)} \sum_{i=0}^{(N_j^1-1)} \sum_{l=i}^{N_j^1} \| \mathbf{X_i} - \mathbf{X_l} \|$$

   where $\mathbf{X_i} \in S_j$; $\mathbf{X_l} \in S_j$; $i = 1, 2, ..., N_j$; $i \neq l$.

   (b) Determine 3 points: $\mathbf{P_j^1}, \mathbf{P_j^2}$ and $\mathbf{P_j^3}$ on the boundary of the cluster S_j such that these three points are far apart from one another, and $\mathbf{P_j^1}$ has the largest distance from the center of gravity Z_j.

   $\mathbf{P_j^1}, \mathbf{P_j^2}$ and $\mathbf{P_j^3}$ are computed as follows. $\mathbf{X_i}$ is a member of S_j.

$$\mathbf{P_j^1} = \mathbf{Z_j} + \mathbf{Q_{max}}$$

   where $\| \mathbf{Q_{max}} \| = max \| \mathbf{X_i} - \mathbf{Z_j} \|$; $i = 1, 2, ..., N_j$.

$$\| \mathbf{P_j^2} \| = max \| \mathbf{D_{min,i}} \|$$

   where $\| \mathbf{D_{min,i}} \| = min(\| \mathbf{X_i} - \mathbf{P_j^1} \|, \| \mathbf{X_i} - \mathbf{Z_j} \|)$; $i = 1, 2, ..., (N_j - 1)$; $\mathbf{X_i} \neq \mathbf{P_j^1}$.

$$\| \mathbf{P_j^3} \| = max \| \mathbf{L_{min,i}} \|$$

   where $\| \mathbf{L_{min,i}} \| = min(\| \mathbf{X_i} - \mathbf{P_j^1} \|, \| \mathbf{X_i} - \mathbf{P_j^2} \|)$; $i = 1, 2, ..., (N_j - 2)$; $\mathbf{X_i} \neq \mathbf{P_j^1}$; $\mathbf{X_i} \neq \mathbf{P_j^2}$.

   (c) Search for 3 points: $\mathbf{L_j^1}, \mathbf{L_j^2}$ and $\mathbf{L_j^3}$, associated with $\mathbf{P_j^1}, \mathbf{P_j^2}$ and $\mathbf{P_j^3}$ respectively, by a method that delineates the convergence of the gravity centers of the subsets of S_j.

   Each subset contains a set of data points enclosed by a circle having the radius (R) a function of idm_j ($\mathrm{R} = \gamma \times idm_j$). γ is a preset value.

   Initially, the search starts at 3 gravity centers: $\mathbf{P_j^1}, \mathbf{P_j^2}$ and $\mathbf{P_j^3}$, and then gradually converges to $\mathbf{L_j^1}, \mathbf{L_j^2}$ and $\mathbf{L_j^3}$, respectively.

   The center of gravity of a subset at iteration t is determined as follows:

$$C_{t-1} = \frac{1}{N_{t-1}} \sum_{\mathbf{X} \in \mathbf{H_{t-1}}} \mathbf{X}$$

   where N_{t-1} is the number of data points in subset $H_{t-1} \subset S_j$ at iteration $(t-1)$.

(d) Determine the Split Threshold ($SpTh_j$) of S_j.
Let $Ld_{\mathbf{X}}$ denote the local density at point **X**. Local density at point $\mathbf{X_j}$ in S_j is computed as follows.

$$Ld_{\mathbf{X_j}} = \frac{M}{\pi(\frac{idm_j}{2})^2}$$

where M is the number of points enclosed by the circle of radius idm_j centered at $\mathbf{X_j}$. And, $SpTh_j$ is defined as

$$SpTh_j = min(Ld_{\mathbf{Z_j}}, Ld_{\mathbf{L_j^1}}, Ld_{\mathbf{L_j^2}}, Ld_{\mathbf{L_j^3}})$$

(e) Single step from the center of gravity $\mathbf{Z_j}$ of S_j to each point: $\mathbf{L_j^i}$, $i = 1, 2, 3$ a distance equal to idm_j, and determine the local density.

If ($Ld_{\mathbf{X}} < SpTh_j$); $\mathbf{X} \in$ {the single step paths between $\mathbf{Z_j}$ and $\mathbf{L_j^i}, i = 1, 2, 3$}

Then { Split S_j , add 1 more new center : $\mathbf{L_j^1}, \mathbf{L_j^2}$, or $\mathbf{L_j^3}$ and go to step 2}

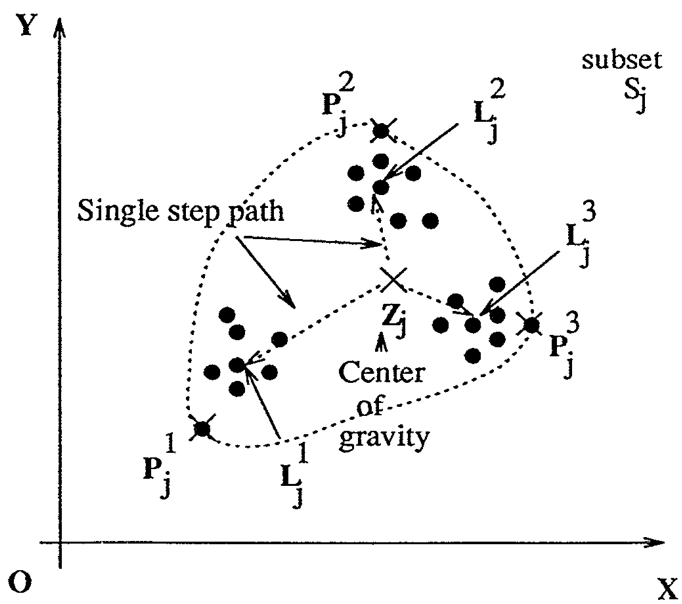

Figure A.1: An example of the cluster S_j where points $\mathbf{P_j^i}$ and their associated $\mathbf{L_j^i}$, $i = 1, 2, 3$ are found in step 4.

5. Determine if it is necessary to merge 2 clusters: S_j and S_k; $j = 1,2,\ldots,N_c$; $j \neq k$.

   (a) Find the Merge Distance Threshold ($Mg\_Dist\_Th_{j,k}$).

$$Mg\_Dist\_Th_{j,k} = min(idm_j, idm_k)$$

   (b) Search for points $\mathbf{X_j} \in S_j$ away from $\mathbf{X_k} \in S_k$ distances $\leq Mg\_Dist\_Th_{j,k}$.

$$\textbf{If} \quad \| \mathbf{X_j} - \mathbf{X_k} \| \leq Mg\_Dist\_Th_{j,k} \; ; \quad \forall \mathbf{X_j} \in S_j; \; \forall \mathbf{X_k} \in S_k;$$

$$\textbf{Then} \quad \mathbf{X_j} \in S_l$$

   where S_l is the subset of S_j.

   (c) Find the Merge Density Threshold ($Mg\_Dens\_Th_{j,k}$).

$$Mg\_Dens\_Th_{j,k} = min(Ld_{\mathbf{Z_j}}, Ld_{\mathbf{Z_k}})$$

   (d) Test the merge condition by comparing the local density at each point $\mathbf{X_l} \in S_l$ with the $Mg\_Dens\_Th_{j,k}$.

$$\textbf{If} \quad (Ld_{X_l} \geq Mg\_Dens\_Th_{j,k}); \quad \forall \mathbf{X_l} \in S_l$$
$$\textbf{Then} \quad \{Merge\}$$

   where $Ld_{X_l} = \frac{M}{\pi(\frac{idm_{j,k}}{2})^2}$, and M is the number of data points in either S_j or S_k. The data points are enclosed by the circle of radius $Mg\_Dist\_Th_{j,k}$ and centered at $\mathbf{X_l}$.

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