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Automatic Extraction of Road Features From Remotely
Sensed Imagery

by
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Abstract

The availability of high resolution (10 m) commercial SPOT satellite imagery allows the extraction of certain planimetric features by manual methods. This thesis experiments with a method to automate the extraction of planimetric road features. In SPOT imagery, roads can be located by using bright narrow Anti-PARallel line segments (apars) as primitive cues. The apars are not perfect cues. Apars are disjoint whereas roads are continuous. There are errors of omission and commission present if apars are the only primary source of information used to identify roads. The thesis identifies and experiments with constraints required to create additional primitives based on the apar primitive. The additional primitives which access global information about features can be used to eliminate the omission errors that are present in the extracted apars; whereas, apars only provide local information. Primitives built from connecting apars together are demonstrated to be sufficient to reason whether or not an apar is a road.

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Chapter 1

Introduction

Automatic planimetric mapping from satellite imagery is difficult because each image can contain many transient features. Mapped planimetric features include natural surfaces (rivers, lakes) and man-made surfaces (roads, railways, bridges). The advantages of automating planimetric feature extraction include: time and labour savings; and accuracy improvements.

It is very difficult to capture and represent in a computer program the necessary expert knowledge required for feature extraction. Human photointerpreters are highly skilled in deriving information yet have great difficulty explaining their reasoning processes at a level required for computer implementation.

A photointerpreter uses all the following types of information in the interpretation of images: shape, size, contextual information, tone (colour), texture, pattern and shadow. Additional clues can be obtained from topographic and temporal information. Certain features, such as roads, appear differently in different circumstances, but each instance has common traits. For a human, it seems easy to extract the relevant information. Whereas for a computer, it is difficult to extract and use the required features.

SPOT PLA imagery is used because of its high spatial resolution and wide visible spectrum. Zelek et al. [51] give the following factors which determine the amount of information that can be extracted from an image:

- The degree of detail available. The degree of detail available in an image depends on the following factors:

the scale or resolution of the imagery.

- the contrast, and
 - the spectral range of the imagery.
- The data extraction method.
 - The skill of the interpreter.
 - The characteristics of the features of interest. Feature characteristics can either be *spatial* such as pattern texture, size, and shape or *spectral* such as intensity (single image) or colour (multiple image).

Image analysis leads to a paradoxical chicken-and-egg problem: How can one interpret before segmenting, and how can one segment before interpreting? Image interpretation can be considered as a mapping between sensory data and an underlying model. This is a search problem. The practical problem in searching is to avoid the combinatorial explosion of possible search paths (matching's).

The automatic recognition and identification of road features from satellite imagery is very difficult. Humans are very good at the recognition of road features, as they identify the local and global constraints quickly and utilize existing context. The automatic extraction of roads from satellite imagery is useful because of the following reasons.

- Road information is needed for the timely update of information systems.
- The labour required to extract planimetric features is reduced with automation.
- Automation helps to maintain *data consistency*, since an automated process is repeatable. Different photointerpreters typically obtain different results on the same scene.
- Road intersections serve as good ground control points for rectification.
- Road networks are useful context for the extraction of other features such as buildings.

One of the cues used in locating roads in SPOT satellite imagery is that roads are usually identifiable by bright narrow parallel linear primitives. The goal of the thesis is to group apart footnote ¹ primitives into new primitives. Apart primitives are grouped based

¹An apart (anti-parallel line pair) is a pair of elongated parallel lines which have opposite direction. The direction of a line segment is defined by the contrast of the region of pixels to the left and right of the line. For example: all lines will have a direction such that the left side is always brighter than the right side.

on proximity and radiometric (gap and respective apar) constraints. An iterative algorithm is developed and shows that new primitives can be created by grouping apars without any domain specific knowledge. It is hoped that the new primitives will provide more global information than the apar primitives provide, in order to provide more cues to be used in an automated process of extracting roads from SPOT imagery.

1.1 Road Feature Extraction Problem

Some of the difficulties in extracting road features automatically from satellite imagery include the following.

- High resolution images tend to be *busy*².
- The feature of interest (roads) may be intermittently visible over the terrain they traverse.
- It seems unlikely that all road classes can be characterized by a simple set of attributes.
- The definition of a road segment is ill-defined.

Roads don't exhibit the same global shape in different images. However, the knowledge required for the recognition of road segments can be structured to aid the recognition process. In a noise-free environment (ideal world), each pixel in a satellite image can be mapped onto a particular real world feature. At 10 m resolution (SPOT PLA), the detection of features² whose dimensions are less than 10 m is only possible if contextual information is introduced. Some roads are barely 10 m in width but are recognizable by the human interpreter. Determining the location of edges to sub-pixel accuracy helps to alleviate the problem of one pixel sharing various feature types. However, classifying individual pixels as road features is error prone because of a lack of necessary information and noise problems.

The *spectral signature*³ of the road and its contrast with the neighbourhood varies throughout the image. There seems to be no unique correspondence between features and

²A pixel can represent more than one type of real-world feature.

³The spectral signature defines the spectral properties of a region. Spectral usually refers to colour. The statistics gathered in our application are only for one spectral band. For one spectral band, better terms include radiometric statistics or brightness statistics. The spectral properties can be characterized by either the mean, standard deviation and number of pixels or the minimum and maximum pixel intensities.

their spectral signature. Different features may have similar spectral signatures while features of the same type may have different signatures. SPOT image data is relatively noisy and sampled at resolutions of 10 (PLA band) and 20 (MLA bands) metres. This constrains the type of features that can be seen.

A road can be defined by its boundary edges. Roads can be characterized as being bounded by elongated parallel lines called *apars* (a pair of anti-parallel line segments). An *apar* is a pair of elongated parallel line segments with opposite contrast. By utilizing structural information, based on the edges in the imagery and the local comparative radiometric contrast, primitive *apar* structures are detected. Two linear segments are paired as an *apar* if the radiometric characteristics between the pairs of lines is relatively constant and the average intensity of the inner region is greater or less than that of the neighbourhood.

In earlier work, the author developed a method for the detection of *apar* segments in remotely sensed imagery [50] based on work done by others [2], [14], [20], [31], [34], [38], [46], [52]. Boldt et al. [2], [46], Scher [38] and Nevatia [31] provide general algorithms for the detection of *apars*. Zhu [52], Majka [20] and Quam [34] use *apars* as cues for the location of potential road segments. Heurtas et al. [14] use *apars* for the detection of airport runways. The detection of *apars* is based on edges detected in the imagery. The edge boundaries are linearized by an iterative endpoint fit algorithm [6]. A boundary curve is broken up into straight line segments which approximate the boundary. *Apars* are detected by pairing up straight line segments which meet certain constraints based on line parallelism, line pair geometry and contrast. An *apar* is classified as being bright or dark. The classification tag of being either bright or dark refers to the relative contrast of the interior region of the *apar* with respect to the immediate surrounding (neighbourhood) region.

The author found that with relaxed threshold constraints, the bright *apar* segments detected in a typical image (image of Madelaine Islands, see Figure 5.1), represented roads with an omission error rate of approximately 20 percent and a commission error rate of approximately 35 percent. The omission and commission error levels assume that all bright *apars* detected were roads. The error levels could be reduced for some scenes by adjusting the threshold parameters. However, the reduction of error levels by the tuning of parameters was image dependent, and could not reduce the error levels below 20 percent. The assumption that all *apars* detected represent road segments is invalid, since *apars* can also represent portions of other narrow linear features such as buildings, railways (of high

contrast) or streams (low contrast apars). What the assumption has shown is that apar primitives offer good cues to begin the search for road detection and recognition.

Grimson [10] categorizes the methods for recognizing a scene object into two groupings:

1. Compute a few descriptors (features) that sharply constrain the identity and/or location of the object. The cost of the search will be greatly reduced at the expense of global preprocessing of the sensory data. The reliance on a few features can make recognition susceptible to measurement noise.
2. Use less distinctive descriptors and rely more on relationships between them to effect recognition and localization.

Apars are less distinctive descriptors and rely more on relationships between them for recognition and localization. Apars do not provide a sharp constraint.

Apars provide a shape cue. There are problems associated with using apars as cues for the extraction of roads.

- Sometimes it is not obvious from a computational viewpoint, which disjoint apars to connect.
- Sometimes different features have similar reflectivity, and the boundary between the two is indistinguishable; for example, certain fields and roads have similar reflectance properties.
- There is significant amounts of uncertainty in locating linear features in satellite imagery.
- The apars detected in the imagery are only as good as the detected edges.
- The segmentation of a boundary curve into straight lines can cause two parallel curves to become non-parallel straight lines.
- Terrain can geometrically alter the shape of certain features; e.g., in mountain regions, road shapes vary with view angle.
- Perturbations (features of a certain class that are slightly different from the norm) can cause problems. An example would be divided highways. One way to handle divided highways is to group parallel narrow linears into another group. In our case we will ignore perturbations such as divided highways.

Apars provide local information. A photointerpreter can make use of global as well as local information. Primitives which combine neighbouring apars into larger groups are required to reason about global information. The apar segments are disjoint. Primitives which establish connectivity among apars are required, since roads are continuous. The development of global primitives is used to make up for the inadequacies that are present in extracting apars.

1.2 What Others Have Done

Some of the different methods used in automated and semi-automated road identification include road finding techniques⁴, road tracking schemes⁵, pixel classification⁶, template matching⁷, map-guided techniques⁸, temporal context guided⁹ and rule-based techniques¹⁰. One of the major problems with most approaches is caused by viewing the world locally as opposed to globally.

Guindon [11] capitalized on the fact that roads exhibit a certain level of invariance when viewed over time in order to find narrow parallel linear temporally invariant features. These types of temporally invariant features were then deemed to be possible road structures.

Schowengerdt [39] argues that automated extraction produces too many false alarms; his approach concentrates on positioning the features. A human operator performs recognition.

Heurtas et al. [14] use apar primitive structures in order to constrain the search in the detection of airport runways. The search space is pruned further by calculating a histogram of the directions of apars and selecting the major directions. Such a pruning of the search space can be done because there are very few runways at an airport and the disjoint pieces that comprise one particular runway will lie on a single straight line. The same constraint cannot be used in road detection since roads can have various directions (including curvature) in a particular image.

Zhu et al. [52] use apars to detect road segments. Various thresholds are selected to

⁴Road finding techniques involve locating, tracking and identifying the road feature.

⁵Road tracking schemes involve tracking the road feature once it has been identified by some other process, such as human supplied control points.

⁶Roads are classified by their spectral signatures.

⁷Roads are identified by correlating a template of a typical road feature.

⁸An existing map is used to help locate road features.

⁹Temporal context guided techniques make use of the fact that certain features (i.e. roads) are temporally invariant.

¹⁰Rule-based techniques organize real world knowledge into rules to guide the search for road features.

grow the road network based on continuity, sharpness, straightness, and divergence. To start the growth of the graph structure, an apar seed is selected. The seed selection is based on selecting an apar, the spectral properties of which, are the closest to the mean of all apars. Longer apars are given preference.

Quam [34] uses a correlation of intensities (road cross-section model) as a road tracking technique.

Wang [45] developed a system for recognizing highways in Landsat TM imagery with accuracies of up to 85 % (omission and commission accuracies). The image is convolved with a Laplacian operator and thresholded to create a binary image. Lines in the binary image are extended in a rule-guided pixel search. Highways have low curvature. The search is constrained by the allowable curvature of a line segment.

Glicksman [9] utilizes various information sources (multi-spectral images, range data, digital terrain models, sketch maps and geographic databases) in a *hybrid control strategy*¹¹ to resolve ambiguities in the edge information. A *cycle of perception*¹² is used to form interpretations of real-image data, including interaction with the user.

Acronym [25],[35] is a bottom-up model-based vision system incorporating four parts: modeling, prediction, description, and interpretation. Acronym recognizes airplanes by using generalized cylinders to model 3-D object parts. One of Acronym's contributions is that it incorporates a general 3-D geometric reasoning capability.

Tenenbaum [42] uses map information to constrain the search for predefined targets. McKeown [27], [28] also utilizes map information to predict the appearance and position of a feature. McKeown's *System for Photointerpreting of Airports using Maps* (SPAM) integrates map knowledge, image processing tools, rule-based control and recognition strategies to label objects and regions appearing in aerial airport images.

Fischler et al. [8] propose a technique for the extraction of road features based on using the F star algorithm. The F star algorithm [8] finds the minimum cost path between two control points. The minimum cost path can be based on the original pixel intensities or a transformed set of pixel intensities. The algorithm is heavily dependent on the selection of

¹¹Glicksman's control strategy is hybrid since it incorporates top-down, bottom-up and mixed control strategies.

¹²A feedback loop used for computer vision. The four stages associated with the feedback loop are cue discovery (object), model invocation (schema invocation), model verification (schema instantiation), and model elaboration (exploration).

a start and stop control point which defines the extent of the road segment. The information used is very localized. Fischler makes the distinction between two different types of operators for the extraction of features. Type 1 which rarely classifies artifacts as instances of the structure they are searching for, but can miss correct instances (Type 1 operators minimize errors of commission). Type 2 which accurately determines relevant parameters of all true instances but may falsely classify and incorrectly parameterize non-instances (Type 2 operators minimize errors of omission). These two types characterize the trade off between omission and commission errors that is present in all techniques.

Grimson [10] studies the use of local constraints to improve the efficiency of matching between sensory data elements and equivalent world models of 3-D objects in a well-defined environment. Grimson concentrates on the localization subproblem (determine rotation and translation transformation in order to match 2D image and 3D model), and "ignores the efficiency of recognizing an object from a large set of possible objects" [10].

Vasudevan et al. [44] address the issues of partitioning and connecting road-like features which appear perceptually continuous in TM and radar imagery. Proximity and alignment (angle) tests are used.

Zhu, Quam, Wang and Vasudevan use techniques that grow apart like primitives using only local geometric information. The presented technique also utilizes radiometric information as well as iterating to continue the growth of the new primitives. The presented technique uses apart primitive attribute information as opposed to local pixel information. Glicksman, Acronym and Grimson give some ideas on how domain specific model knowledge can be incorporated into the analysis procedures.

1.3 Issues Not Addressed

Some issues related to the automatic extraction of road features from satellite images not addressed in this thesis, include:

- **Scale (resolution).** SPOT PLA imagery has 10 m resolution. The PLA imagery can be undersampled to coarser resolutions. This type of approach has been ignored for road features. The detection of edges in the image by the edge detection process is only done at one level. Coarse to fine edge resolution can be obtained by convolving

the image with different sized *Difference of Gaussian*¹³ (DOG) filters. A single size DOG filter is chosen for the road extraction analysis (assuming road features have widths between 10 m and 35 m).

- **Projection.** The digital image used for analysis is a flat projection of a portion of the curved world. The type of projection used is ignored. The issue of changing projections is relevant because of the approach taken. The detection of road features is based on linearizing the edges. A straight line in one projection will not necessarily be a straight line in another projection.
- **Uncertainty models.** The inclusion of a particular model of uncertainty such as Bayesian, Dempster-Shafer or Fuzzy Logic is ignored.
- **Absolute reflectance.** Since the analysis work is based on using relative pixel intensity values in comparison to other pixels in the scene, there is no need for absolute pixel reflectance. Absolute reflectance measures can be obtained by applying radiometric and atmospheric correction techniques to the image.
- **Viewpoint.** A nadir-looking SPOT PLA image is ideal for the extraction of road networks. Off-nadir images can be transformed to ortho-images, but it is possible to introduce various imperfections into the image (e.g. a side view could cause the occlusion of a portion of a road segment due to trees, shadows or other neighbouring features). Different 2D views of a 3D object may produce different shapes. Another example of how the view angle determines the shapes of roads are switchbacks on the side of a mountain: the road may disappear from view.
- **Digital Elevation Models (DEM).** Elevation information can constrain the search for road segments since roads typically have a maximum grade.

¹³The DOG filter was found by Marr and Hildreth [23] to be a suitable approximation to the Laplacian of a Gaussian filter. The Laplacian of a Gaussian is the minimal uncertainty filter where minimal uncertainty is a measure of tradeoff between localization in space and localization in frequency. The Laplacian of a Gaussian operator fulfills the following two requirements for detecting intensity changes: isotropic linear differential operator which takes the second spatial derivative of the image; and the filter can be tuned to act at any desired spatial frequency. The results are well behaved (i.e. no new zero crossings appear at different scale spaces). The Laplacian operator is the only isotropic (orientation independent) linear second derivative operator. The Laplacian of Gaussian operator is not the best operator with respect to localization in space, particularly for rounded edges with large curvature [43].

- **Other image input.** SPOT PLA imagery was chosen because of its high spatial resolution and wide spectral coverage. Other spectral information can be obtained from the SPOT MLA1 and MLA2 bands, and the near-infra-red band MLA3.
- **Illumination.** Shadows can complicate the extraction of road features. Roads can become undetectable in shadows. Shadows and other illumination effects are ignored.
- **Context.** Context can assist in the detection of road features. For example, buildings are located near roads and roads are not in water. Representations have not been developed to exploit this level of contextual information.

1.4 Vision Problem

Remotely sensed images are sets of measurements of certain properties of real-world features. The vision problem concerns itself with the interpretation of those measurements.

The various tasks in a vision system involve:

- **Recognition:** What is it? What type of object features to search for in the imagery? Mapping of primitives into real-world features is a problem of recognition.
- **Localization:** Where is it? The development of primitive cues constrains where to begin to look and where to look next.
- **Inspection:** Detailed analysis is required to confirm and verify the location and classification of a particular feature.

There are three basic methods of vision control:

1. The **Bottom Up** method is image data driven. The state of the data determines the course of action.
2. The **Top Down** method can either be top-down parsing or expectation driven control. Top-down parsing uses model knowledge at each stage to decide how to move down a hierarchical knowledge-base. Expectation driven control uses the *principle of least commitment* [21] and thresholds are relaxed as expectations arise.
3. **Mixed: Bottom Up and Top Down:** This has generally been the method that has been widely accepted, except that there is no clear view on how to integrate the two techniques into a unified process.

1.4.1 Segmentation of Image

Analysis of the image requires the image to be transformed into some manageable abstraction. The method used is based on the Marr-Hildreth [23] edge detection technique. The edge detection method has been used for deriving Digital Elevation Models (DEM) from a pair of different viewpoint SPOT PLA images at MacDonald Dettwiler [5]. One of the criticisms of edge detection is that it is very sensitive to noise. To overcome noise problems, the edge detection process is done at different spatial resolutions.

According to Marr [22], the intensity changes in an image are a result of:

- illumination changes, which include shadows, visible light sources, and illumination gradients,
- changes in orientation or distance from the viewer of the visible surface, and
- changes in surface reflectance.

Roads produce intensity changes due to a change in surface reflectance between the road and neighbouring features.

Marr convolves the image with several different DOG filters. We only use one DOG filter. The spatial resolution of the SPOT PLA data (10 m) and the width of the road features in SPOT PLA imagery (10 m to 30 m) constrains what edges can be identifiable at different DOG resolutions. A DOG filter with Gaussian sigma values of 1.0 and 1.5 are used. All zero-crossings are identified and checked to see if they are significant¹⁴. A hysteresis threshold is used to hypothesize whether a zero-crossing is significant. Firstly, a zero-crossing is identified as a potential horizontal or vertical edge. The mean of the region (original input image), to the right of the edge is compared to the mean of the region to the left of the edge. If the difference of the two means is greater than the lower threshold value, then the zero-crossing is labelled as a plausible edge; else, it is rejected. The zero-crossings are labelled as either plausible horizontal or vertical edges by looking at the neighbouring region means in two passes (one horizontal pass and one vertical pass). Zero-crossings that are greater than the upper threshold value are identified as edges. Any plausible edges that are neighbours of identified edges are also labelled as edges. The edges are linked

¹⁴At a particular DOG filter resolution, all zero-crossings are significant. In this case, significance refers to the elimination of zero-crossings that are due to noise as opposed to natural phenomenon.

into boundary segments. The method used for edge detection does not necessarily result in closed contour edges.

1.5 Summary

The main thrust of the thesis is to develop higher level primitives from apars. The role of the higher level primitives is to facilitate obtaining global information. Apars only concern themselves with local properties. The following gives a brief description of the thesis contents:

- In order to identify a feature in any image, one has to define what the feature looks like. Chapter 2 talks about a road's definition in general terms of its appearance in SPOT PLA imagery. The definition of a road dictates what knowledge is required for its recognition. Road knowledge indicates what type of information (primitives) is required for reasoning about a road's presence and location. Apars provide local cues for road detection. Global primitives also are required.
- Chapter 3 describes the different primitive levels (i.e. apar segments, collinear-segments). The primitive attributes are described along with their importance. Discussion also includes the information primitives provide.
- Chapter 4 deals with the constraints used to develop collinear-segments and segments from apars. The algorithm that uses the constraints is presented.
- Chapter 5 presents the results of the algorithm. Tables show which constraints were executed and for how many iterations. Illustrations show where the algorithm succeeded and failed.
- Chapter 6 discusses performance of the algorithm and what modifications might be required. A discussion follows regarding additional work required to further automate road extraction.

Chapter 2

7

What and Where?

Identification of roads in SPOT satellite imagery, requires answers to some fundamental questions about roads. *What is a road? What do roads look like? Where are roads located?* The answers are constrained by the domain of the input image source (SPOT PLA).

2.1 SPOT Imagery

One of the prime objectives of the SPOT program is to achieve planimetric cartography at 1:250,000 scale and cartographic updating at 1:100,000 and 1:50,000 scales [4].

The SPOT satellite consists of two identical High Resolution Visible (HRV) range instruments. There are 3 multi-spectral bands (Multi-spectral Linear Array 1,2,3 *MLA*) which have a nadir ground sampling interval of 20 m. The Panchromatic Linear Array (PLA) band (black and white mode) has a nadir sampling interval of 10 m.

The characteristics of the different bands as given by Chevrel et al. [4] are as follows:

- *MLA1*: green (500 to 590 nm) band is centered around 550 nm. This band gives access to turbidity assessment and bathymetric evaluation in the first 10 to 20 m in clear water.
- *MLA2*: red (610 to 680 nm) band is similar to Landsat TM band 5. This band is used for information on crop identification, bare, and oily rock surfaces. Vegetation has low reflectance in this band.
- *MLA3*: near infra-red (790 to 890 nm) band. Vegetation typically stands out brightly while water appears very dark.

- *PLA*: panchromatic (510 to 730 nm) band. Used to retain higher capability for texture analysis in support of the colour mode and higher information content over vegetated areas. The *PLA* band corresponds to the same spectral range as panchromatic aerial film.

2.2 What is a Road?

A road is a land transportation route for man-made vehicles (i.e. cars, trucks). Roads can be covered with various substances such as asphalt, dirt, gravel (rocks), concrete and various combinations of the above and other materials. A road is relatively flat along its width, but can be banked on curves. Traffic flow can be either one-way or two-way on one or multiple lanes.

In order to automate the extraction of road features from SPOT imagery, it would be advantageous to utilize some of the cues that a photointerpreter uses in manually identifying road features. What does a road look like in SPOT *PLA* imagery? The properties of roads will vary with different sensor types and different resolutions of imagery.

Features are mainly identified by two primary spatial factors: shape and pattern. Apar-like structures (shape) identify roads. Roads intersect other roads and form a network structure (pattern) in the satellite image. Linears, such as roads, are the most easily identifiable features in any image. Patterns involve a more global overview of the imagery. An example pattern is an urban region. The urban region has a distinct texture which gives contextual information for the further analysis of (in our case) road features.

The characteristics of what a road looks like are divided into the following five categories:

1. Radiometric:

- In aerial photographs, a road typically exhibits higher reflectance than the surrounding terrain. An exception would be highways in a desert (in this case, the surrounding terrain has a higher reflectance).
- Roads made of the same material will exhibit similar reflectance.
- Roads usually have a smooth surface.

2. Geometric (local):

- Road boundaries can be identified by two anti-parallel edge segments (apars).
- Roads form highly elongated regions.
- Roads are generally of fixed width. The local width of a road usually remains constant.
- Roads are continuous.
- Roads tend to remain flat.
- Roads usually have a maximum curvature, except at road junctions. An exception includes mountainous terrain where switchbacks may have high curvature.

3. Structural (global):

- Roads are connected to other roads at junctions. Roads intersect at arbitrary locations with other roads. For the general case, the angles of intersection cannot be constrained.
- Intersections of less than 45 degrees are rare. Exceptions include highway off ramps and road splitting (i.e. becoming a divided highway from a non-divided highway).
- Roads form a graph structure (network), which can be represented by nodes and arcs. The arcs correspond to road segments while the nodes correspond to road intersections.

4. Contextual:

Contextual information can be broken into two categories:

- Road features have certain spatial relations with respect to other features such as buildings and water;

Roads are not located in regions of water.

Roads may cross water regions (bridges, tunnels, ferries).

Roads may pass through tunnels in mountainous terrain

Buildings are located near roads. Access to buildings is usually provided by roads.

Roads provide access to farm fields.

- Road features can also have spectral, geometric and structural constraints in certain contexts such as urban or rural areas:

- urban areas:

- * Grid patterns are prevalent in suburbs.
- * Road sides may be blurred by buildings.

- farmland:

- * Roads are typically long straight sections.

- * ~~Roads usually form a wide grid pattern separating farm fields.~~

- * Road definition may be vague at times. Certain crop types may exhibit similar reflectance properties as the road surface, making the road indistinguishable from the neighbouring features.

- forested areas:

- * Roads can be obscured by the forest canopy.
- * The contrast of the road is usually strong.

- flat terrain:

- * Roads usually have very few curves.

- hilly, mountainous terrain:

- * Windy roads can exist (i.e. switchbacks).

5. Knowledge from Additional Information Sources:

- If a DEM is available, then roads can be constrained by a maximum grade.
- Depending on the accuracy and resolution of the DEM, it is possible to make use of the fact that some roads are banked on curves.
- If provisions are made for occluding surfaces and shadows, then the knowledge that relief displacement may obscure road sections can be used.

Use of contextual information requires extraction of other features, which is beyond the scope of this thesis. Additional information can be obtained from other sources (including elsewhere in the image), but it was decided to concentrate on efforts to hypothesize additional information from cues such as apars.

In order to reason about what exists in an image, extracted primitives are required. The primitives must support deductions based on road feature knowledge. Road primitives are mainly identified by their shape. Apars can be used for making local inferences (i.e. roads brighter than neighbouring regions), but additional primitives are required to make global inferences (i.e. roads are continuous). The additional primitives refer to the primitives formed by connecting neighbouring apars. Apars alone do not present enough information to deduce whether the apar is a road.

Chapter 3

Knowledge Representation

Different representations make different items more (or less) accessible. In order to reason about real-world features, sufficient information is required. The primitives provide the cues for the mapping of primitives into real-world features.

3.1 Primitive Dimension

3.1.1 Levels

The apar primitive structure offers cues on potential locations for road segment features. The apar is a bar type structure as typified in Marr's primal sketch. The apar primitive is primarily identified by shape. Apars are disjoint, whereas narrow linears (specifically road segments) are continuous and form graph-like structures. Primitives that are formed by domain independent apar combinations, are used to further constrain the possible real-world mappings of extracted primitives. The lowest level primitive is the pixel primitive. Lower level primitives inherit the properties of their parent primitive. An apar can map into a set of possible real-world features. A segment (a collection of collinear apars) may map into a smaller set of real-world features.

The hierarchy of primitive descriptors follows in ascending order as they appear in the primitive hierarchy.

- **Pixel.** The pixel is the lowest level element which defines the resolution of the input image.
- **Edge.** The image is convolved with a Difference of Gaussian (DOG) filter. The zero

crossings represent the edges (discontinuity of intensity value) in the image according to the resolution as determined by the size of the DOG filter.

- **Boundary.** A boundary is a set of linked edge points. The edges are based on detecting the zero-crossings in the DOG filter convolved image. The zero-crossings are linked together into boundary segments. The boundary segments have associated properties that indicate the spectral properties to the left and right of the boundary segment.

-
- **Straight line.** In order to simplify processing in the parallel grouping procedure, the boundary segments are linearized into straight line segments. Each individual boundary segment is split into a set of linears (straight lines) based on an iterative endpoint fit algorithm [6].

- **Apar.** Parallel straight lines are paired into apars. Apars provide road segment location cues. The pairing process is based on the following properties: line parallelism, line pair geometry and contrast. The algorithm does not make provisions for apar structures sharing common line segments with other apars and the possibility of redundant apar information. Redundant apars are a group of 3 or more apars that can be represented just as easily by two apars. Before apar segments are linked together, the apars go through a cleaning process so that there is no overlap between them.

The process that cleans up the set of apars for further processing is broken up into two stages: (1) remove the redundant apar structures (see Figure 3.1); (2) group apars that share a common side (see Figure 3.2). After the apar segments are cleaned, further processing (linking apar segments together based on other information) can commence.

The center medial axis is used to represent the apar structure. To simplify further processing (development of higher level primitives based on the apar primitive), the representation of an apar is a line segment.

- **Segment.** A segment is a set of connected apar structures. The segment ends when it intersects another segment, stops at the image boundary or ends abruptly.
- **Collinear-segment.** A collinear-segment is a set of collinear apar segments. Collinear-segments give more general trends and patterns with a global viewpoint as

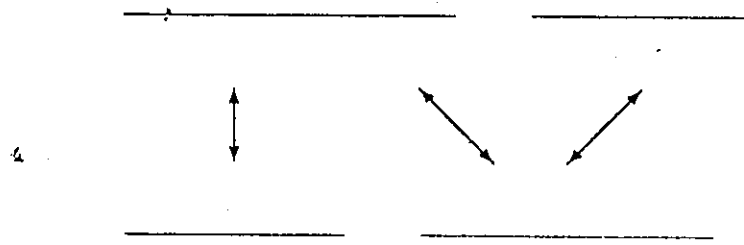


Figure 3.1: **Redundant Apars:** The arrows identify the lines that are paired into the apar structures. Initially there are three apars. The middle grouping can be eliminated and no information will be lost.

compared to segments. Collinear-segments may traverse intersections and can only represent one particular feature type (i.e. road).

- **Network (Graph Structure).** "A graph is an ordered triplet $(V(G), E(G), I(G))$, consisting of a non-empty set $V(G)$ of vertices, a set $E(G)$, disjoint from $V(G)$ of edges, and an incidence function $I(G)$ that associates with each edge of G an unordered pair (not necessarily distinct) of vertices of G "[3]. In most instances a road graph will be planar (i.e. no bridges over roads). Certain context and texture clues can constrain the graph's topological properties. Different regions such as urban, rural, and mountainous terrain have distinguishable road patterns.

The hierarchy of primitive structures is interlinked by pointers (i.e. an apar points to the two straight lines that were paired) to provide bidirectional movement through the hierarchy as more detail or abstract information is required. Redundancy is reduced in the hierarchy by storing pertinent information at the most appropriate level. The data structures that link the hierarchy together allow for easy access to relations within the hierarchy. The data structure facilitates determining what boundary structure a straight line originated from. If a straight line points to the boundary structure it originated from, then it can be determined what other straight lines (neighbouring straight lines) came from the same

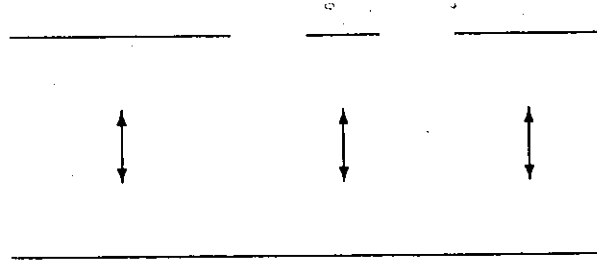


Figure 3.2: **Apars Sharing A Common Side:** The arrows identify the lines that are paired up into apar structures. Initially there are three apars. The top three lines can be connected to form one line, thus creating a new apar. The initial three apars are eliminated.

boundary segment (i.e. by following sets of pointers from one structure to another). The apar's attributes point to the 2 straight lines which were grouped together to form the apar structure. Thus, it can be determined by following the relevant pointers, what apars have sides that come from the same boundary segment.

3.1.2 Primitive Attributes

Each item (not including pixels) within the primitive hierarchy has a set of associated attributes. Besides attributes, each level is interlinked with its parent and child (up and down the hierarchy) primitive. The reason for having a set of attributes stored is to increase performance in subsequent processing by not re-calculating attribute values.

The attributes of a straight line are as follows.

- **Identifier.**
- **Length.** The length of the line segment is in pixel coordinates. If straight lines were perceptually grouped together, the length and angle would be required for measures of collinearity.
- **Angle.** The angle of the line defines the direction. The direction is with respect to the coordinate system chosen. The top left corner pixel's coordinates are (1,1) and

the bottom right corner pixel's coordinates are (512,512) for a 512 by 512 pixel image. The x axis (pixel axis) is positive in the direction from the top left corner to the top right corner. The y axis (line axis) is positive in the direction from the top left corner to the bottom left corner. The direction of a straight line is defined by the ordering of the endpoints. The straight line's direction travels from point 1 to point 2.

- **Radiometric Statistics.** The mean, standard deviation and number of pixels to the left and right of the straight line are stored. These statistics are used when pairing up straight lines into apars in order to check for spectral uniformity within the proposed apar interior region.
- **Pointers.** There are pointers that reference the edge structure information. A straight line is an approximation of a set of connected edge points. The spatial location of the edges that make up the straight line segment can be referenced by pointers.

There are two types of apar structures: real and deduced. Real apars are apars that have been extracted by pairing up two linears. Deduced apars are created by combining neighbouring apars. Two different types of structures exist because the preliminary apar structure does not provide the mechanics for storing the necessary information about deduced apars (constrained by the original software).

Apar properties include the following.

- **Identifier.**
- **Length.** The length attribute of an apar is used in the calculation of collinearity between neighbouring apars.
- **Width.** The width attribute was not used as part of the constraints in establishing connectivity amongst disjoint apars. The width attribute was included since it defines, with the length attribute, the shape of the apar.
- **Radiometric statistics** of the region inside the apar structure. If a certain type of road has a definite spectral distribution, then all apars with that response can be similarly classified. It was decided to only store the mean, standard deviation and number of sample points in order to minimize memory storage costs. The image

data is typically noisy, and the stored information would suffice in order to properly categorize a particular apar's spectral properties.

- **Contrast.** The apar can be classified as dark or bright with respect to the immediate neighbouring region. Using knowledge that roads are typically bright apar regions, requires quick access to this type of information.

-
- **Contrast Strength.** Based on predetermined thresholds, both straight lines can be classified as strong or weak with respect to the contrast difference across the straight line. Apars are then classified as strong-strong, strong-weak, weak-weak, or undetermined.

It was originally thought that only strong-strong bright apars would be used as candidates for road segments. The candidate space used for potential road segments were all the bright apars. The contrast strength gives an indication of edge strength for the apar. It is possible to use the contrast strength as a measure of certainty (i.e. strong-strong bright apars are highly more likely to be roads as compared to weak-weak bright apars), but this avenue was not explored in the tests conducted.

- **Pointers.** Pointers indicate which two straight lines were paired up to create a particular apar. This allows access to information about the straight lines attributes, and even the actual edge information (traversing the hierarchy). There is also a field which indicates the relative orientation of one straight line with respect to the other (i.e. if they are pointing in the same relative direction).

3.1.3 Primitive Information

The choice of primitives for road extraction is determined by the knowledge required to recognize road features in SPOT PLA imagery.

The apars provide local information. Only bright apars are used because typically roads in SPOT PLA imagery are bright parallel narrow linears. The geometry of an apar satisfies the definition of what a parallel narrow linear is.

The global primitives (segments, collinear-segments) provide a more global viewpoint on the information. Highly elongated continuous regions (i.e. roads) can only be determined from global primitives. Curvature attributes can be calculated from collinear-segments.

Structural information such as types of intersections, the formation of graphs and networks can be determined by examining the relations of higher level primitives.

There is some information that is inherent within the hierarchical structure. A boundary segment is linearized into a set of straight line segments. Each of the straight line segments can be paired with another straight line segment to make an apar. Apars formed from the same boundary segment are possibly connected. Other primitive information is obtained from basic classification techniques. Roads cannot be classified in an image by thresholding techniques, since spectral properties for roads are only locally consistent.

A particular case where classification techniques yield useful information, is where the definition of a gap region between two apars is uncertain. Are the two apars part of a larger primitive feature? *Threshold classifying*¹ the gap region between two apars based on the spectral information provided by the two apar interior regions, provides a measure of similarity of the gap region with respect to the two apars it may connect.

Proximity and collinearity constraints are used to interconnect disjoint apars. Additional low level information is used to verify that the connection is plausible. Types of evidence that validate the plausibility of an interconnection are as follows.

- **Edge boundary information.** The apars detected are deduced from the pairing of parallel straight lines. Straight lines are extracted by the process of linearizing a boundary segment. It is possible for straight lines from the same boundary segment to belong to different apars. If straight line *L1* and straight line *L2* are from boundary *B1* and linear *L1* forms apar *A1* and straight line *L2* forms apar *A2*; then there is a possibility that apars *A1* and *A2* should be connected. This type of information lends evidence to support certain apar groupings.
- **Local spectral classifications.** A similarity of the spectral signature of the region between apars (gaps) provides evidence that the two adjoining apars should connect.

The algorithm for connecting disjoint apars uses spectral classification information to verify possible interconnections.

¹Threshold classifying a region refers to binary classifying a region based on a training signature. All pixels with an intensity value which is between a predefined minimum and maximum pixel intensity are marked as true and all others are marked as false.

Chapter 4

Developing Global Primitives for Road Extraction

Perfect segmentation is not possible due to noise and other factors present in the imagery. Primitives are created by grouping the edges produced by the edge detection process. Apar primitives are extracted, but they are usually discontinuous. Apars do not provide enough information as cues to reason about road identification. Additional primitives which provide global information need to be created from apar primitives: segments and collinear-segments.

The extracted primitives should allow graceful degradation if a certain piece of information is missing in order to determine reasonable mappings into real-world features. In developing segment primitives, the goal is to combine apars into larger domain independent primitives of the same feature type.

4.1 Constraint Satisfaction Problem

The search space for matching primitive elements to equivalent world model elements is extremely large and to control the potential combinatorial explosion, constraints are required. Constraints are also needed in order to develop global primitives from apars. Trying all possible apar connections would be expensive from a processing point of view.

Constraint satisfaction is a problem of simultaneously satisfying the constraints imposed by the cues. Mackworth [17] defines the Constraint Satisfaction Problem (CSP) as: "Given a set of n variables each with an associated domain and a set of constraining relations each

involving a subset of the variables, find all possible n -tuples such that each n -tuple is an instantiation of the n variables satisfying the relations". There are two classes of CSP's:

- **Boolean constraint problems** (the constraint is either satisfied, or not satisfied); and
 - **Numerical optimization problems**, where the goal is to design a system to maximize the extent to which the solutions it provides, satisfy a large number of local constraints.
-

The algorithm which connects apart uses both boolean constraints and numerical optimization constraints. Mackworth and Freuder [19] have shown that arc consistency (with respect to a graph's node, arc, path) can be achieved in a time linear in the number of binary constraints.

Grimson [10] lists some of the traits that constraints should have:

- constraints should be coordinate frame independent,
- constraints should be simple and have low computational cost,
- constraints should be as powerful as possible in the sense of removing large portions of the overall search space,
- constraints should degrade gracefully in the presence of error, and
- constraints should be independent of the specifics of the sensor.

Constraints can either be based on positive information or negative information. An example of positive information would be the extraction of apart primitives which constrain the search for road features. An example of negative information can be the classification of the geo-system in order to separate water and land. Water regions prune the search space for road features.

4.2 Perceptual Constraints (Groupings)

The process of perceptual organization is used to form groupings of various shape structures in the image based on primitive information. Various image groupings of primitives include

groupings based on connectivity, collinearity, parallelism, texture properties and certain symmetries.

Apar structures are detected by grouping parallel line segments. The collinear-segment primitive is a collinear grouping of apars. A segment is a subset of a collinear-segment. A segment terminates at an intersection. Similar procedures are used for combining apar primitives into collinear-segments and segments. The only distinction between the two ~~would involve the location of an intersection. An intersection involves the meeting of 3 or~~ more apars (segments, or collinear-segments).

We are not concerned with the actual definition of the region between apars but rather the apars which interconnect. Due to inadequacies in the edge detection phase and subsequent linearization and parallel grouping, the gap region between 2 apars is not identified as an apar.

4.3 Grouping Apars into Segments

4.3.1 Constraints Used

The grouping of apars into collinear-segments is constrained by various parameters (and functions). The only consideration in grouping apars is the handling of connections amongst apars. Apars meet one another at *intersections* or along a collinear path.

- The *no-intersection* case involves two apars meeting one another. The two apars are of the same feature type (i.e. road). The apars that are connected are collinear. The two apars can be along a straight line or can form a curved portion of a feature type (i.e. road).
- The *intersection* case involves the meeting of three or more apars at a common point. There are two different types of intersections.

The *t-junction* intersection involves the meeting of three apars at a common point. It is possible for an apar to intersect another apar along its length as opposed to the endpoint.

The *multiple-junction* intersection case involves the meeting of more than three apars at a common point. Multiple-junctions are treated as sets of t-junctions where the connection is always made at the endpoints.

No domain dependent knowledge is used in connecting apars. In certain situations it would be advantageous to include domain dependent knowledge. An example would be the intersection of a road and a railway. If the railway crossed the road on a bridge, it is not obvious that the two sections of collinear road are of the same feature type (road). Knowing that the linear section is a railroad, the bridge's existence can be deduced, and it follows that the two sections of road are interconnected based on collinearity and proximity. To achieve this type of reasoning strategy requires reasonable robustness on the part of the hierarchy of primitives.

The constraints used are as follows.

1. **Work space.** Theoretically, all detected apars are possible candidates. In SPOT PLA imagery, roads are typically bright narrow linear features. The work space for road features are the bright apars. Dark apars are not included.
2. **Search Constraint.** The search for potential candidates is constrained to a predefined region. Only the apars that are in close proximity to the reference apar are likely candidates. A search is made from each endpoint of the reference apar in the direction of the apar (based on the angle of the apar medial axis) with a search radius of r and a search angle of 2θ (see Figure 4.2).

In order to find candidates efficiently, the apars are spatially indexed. A simple method is used for spatially indexing apars. The apar center line is mapped into a raster domain in which each pixel occupied by the apar centerline has the value of the apar identifier.

3. **Apar Radiometric Compatibility Constraint.** The potential apar candidate is tested for radiometric compatibility with the reference apar. The radiometric properties of the candidate apar should be similar to the radiometric properties of the reference apar. This is accomplished if either equation 4.1 or equation 4.2 is satisfied (where k is some constant, in our tests k was set to 1). The mean and standard deviation (μ and σ) are used (as opposed to minimum, maximum values) in order to de-emphasize the noise in the imagery. Candidates that do not meet this constraint are pruned from the search space.

$$\mu_{ref} - k\sigma_{ref} \leq \mu_{can} \leq \mu_{ref} + k\sigma_{ref} \quad (4.1)$$

$$\mu_{can} - k\sigma_{can} \leq \mu_{ref} \leq \mu_{can} + k\sigma_{can} \quad (4.2)$$

4. **Gap Radiometric Compatibility Constraint.** This constraint checks to see if the gap region is radiometrically compatible with the reference and candidate apars (see Figure 4.3). Radiometric compatibility is determined if equations 4.3 and 4.4 are satisfied (similar to the apar spectral compatibility constraint, a value of 1 was used for k). This is similar to checking the compatibility of reference and candidate apars, except that the gap region is treated as an apar and checked to see if it is compatible with the reference and candidate apars. If the gap region is not compatible with either the reference or candidate apar, then the candidate is pruned from the search space.

$$\mu_{ref} - k\sigma_{ref} \leq \mu_{gap} \leq \mu_{ref} + k\sigma_{ref} \quad (4.3)$$

$$\mu_{can} - k\sigma_{can} \leq \mu_{gap} \leq \mu_{can} + k\sigma_{can} \quad (4.4)$$

5. **Angle Constraint.** The angle of the apar is used to determine the type of connection between the two apars. The minimum acute angle between the reference and candidate apars falls between a minimum and maximum threshold value. The different types of connections that can be made amongst disjoint apars are as follows (see Figure 4.1).

- **Collinear.** A collinear connection is the connection of the endpoint of the reference apar to the endpoint of the candidate apar. A collinear connection (i.e. along a straight line) is made if the acute angle between the reference and candidate apars is between 0° and 30° .
- **Normal.** The reference apar's endpoint can be extended to form a normal to the candidate apar's centerline at a point other than one of the two endpoints. The normal line is the connection between the reference and candidate apar. The acute angle between the reference and candidate apars is between 60° and 90° .
- **Perpendicular.** If one of the constraints for the normal case fails then a perpendicular connection is made. A perpendicular connection consists of two line segments. The reference apar is extended until it intersects the extended candi-

date apar. The constraints for a perpendicular connection are that neither the normal nor collinear case are applicable.

A test on the similarity of the angle of the line that connects the two apar centerlines with respect to the reference and candidate apar angle was tried, but was found to be too sensitive to be useful.

6. **Gap Collinearity Constraint.** From the list of candidates left, the best one that minimizes the criterion function 4.5 or 4.6 (depending on the circumstances) is selected. A maximum threshold value is set in order to prune candidates. If the left hand side of equation 4.5 or 4.6 is greater than 1.0, then the candidate is pruned from the search space. The function tries to minimize the gap distance relative to the length of the reference and candidate apars. *Gap* refers to the distance between the apar centerlines, as shown by the bold line in Figure 4.1. l_{ref} is the length of the reference apar. l_{can} is the length of the candidate apar. Equation 4.6 is the special case where a normal type connection is made between the reference and candidate apar.

$$\frac{gap}{\min(l_{ref}, l_{can})} \quad (4.5)$$

$$\frac{gap}{l_{ref}} \quad (4.6)$$

If the two apars are connected (for collinear and perpendicular type connections), the new length of the apar would be the sum of the two individual apar lengths. There is a maximum threshold value for the criteria function in order to prune candidates that are highly unlikely to connect (value of 1.0 was used). It is not always the case that an apar will connect to another apar.

7. Collinear-segments have no intersections with other collinears, therefore each endpoint can only connect to one other apar.

Applying the above constraints yields the collinear-segments that:

- determine the connections between apars, that were not picked up by the edge detection process or were disregarded by the linearization simplifications; and
- determine the connections between apars where the gap region is not defined by its edges but spectrally similar to the 2 apars it joins (i.e. road and neighbouring field

has similar spectral reflectance).

4.3.2 Algorithm

Creating global primitives from apars requires establishing connectivity amongst neighbouring apars. The constraints in the previous section are used to establish that connectivity. The algorithm that was tested uses the constraints in order to determine which apars combine to form segments and collinear-segments.

Before presenting the algorithm, some terminology requires clarification. The connections between apars are based on interconnecting apar centerlines. There is a status associated with each apar. Only the apars with an active status are considered (e.g. an apar will have an inactive status if it was eliminated when the redundancy check was done). Since only the bright apars are being considered, all the dark apars have been pruned by giving them an inactive status. The acute angle between two apar centerlines has a range of 0° to 90° . The algorithm is as follows:

1. for $i = 1$ to all apars (real and deduced) with active status do step 2.
2. for $k = 1$ to 2: (the two endpoints of the apar centerline):
 - Verify that the apar endpoint has not been connected to any other apar. A list keeps track of all connections. If a collinear or perpendicular connection is made between two endpoints, then those two endpoints are marked as used. If a normal type connection is made from an endpoint to a line, then that point is marked as used. For normal and perpendicular type connections, it is allowable for the candidate endpoint to be already used in another connection. A collinear type connection can only be made if the reference endpoint and candidate endpoint have not been used in any other connections. These rules are in place to constrain the intersections possible. A more elaborate model might take into consideration all possible combinations and require domain dependent knowledge.
 - For all real and deduced apars, find the apars that are in close proximity to the endpoint of interest. A circular arc region is searched with the center point being the reference apar's endpoint. The direction of the search arc is in the same direction as the reference apar. The search arc has a radius of 20 pixels

and an arc separation of 90° . A separate list is kept for both the real apars and the deduced apars.

- All potential candidates found are sorted with respect to minimizing the gap collinearity constraint (equations 4.5 and 4.6).
 - When all candidate apars (real & deduced) are located and sorted, then do step 3.
3. for $l = 1$ to all candidate apars (deduced and real), do the following steps (deduced apars are looked at first, because they are created from combining other apars and are therefore probably more significant):
- Determine which type of connection exists between the reference and candidate apar. The different types of connections amongst neighbouring apars, as mentioned earlier, are collinear, normal and perpendicular (see Figure 4.1).
 - Determine the statistics of the gap region. For each of the three different types of connections, the gap region will take on a different shape (see Figure 4.1).
 - Determine if the candidate apar satisfies all the constraint tests to allow connection to the reference apar:
 - Verify that the candidate endpoint is not marked as connected. The verification of the reference endpoint was initially made at one of the outer loops (Step 2). The verification of the reference endpoint has to be re-initiated at each instance of trying to pair up a candidate with the reference. Once a candidate connects to the reference, the endpoints are marked accordingly; if the reference is marked as used, then there is no need to continue checking other candidates and the loop (Step 3) can terminate. For perpendicular type connections, it is allowable for the candidate endpoint to be used. The relaxation of the constraint on perpendicular type connections allows the formation of multiple intersections.
 - Verify that the candidate's endpoint of interest is actually the closest point of the two candidate endpoints with respect to the reference endpoint. This allows correct alignment of the two apars to be connected.
 - Apply the gap collinearity constraint. Prune choices that are less than a pre-set threshold value (i.e. we use 1.0). Note that all the candidates have been

ordered in the list with respect to minimizing the gap collinearity constraint cost (see equations 4.5 and 4.6).

- Apply the apar similarity constraint. Reject candidates that do not meet this constraint.
- Apply the gap apar similarity constraint. This is the most expensive constraint and justifiably placed last. The statistics have to be collected for the gap region during the execution time. Reject candidates that do not meet this constraint.
- If all the constraints are satisfied, then do the following:
 - Update the length of the apar if the connection type is collinear or perpendicular. The length of the apar is the sum of the reference apar length and the candidate apar length. The redefining of the apar length incorporates more global information to be used when evaluating the Gap Collinearity Constraint in subsequent iterations.
 - Connect up the apar centerlines according to the type of connection.
 - * Normal case: Connect the reference endpoint on a line that is normal to the candidate apar's centerline. The interconnection is the normal line.
 - * Perpendicular case: Intersect the reference and candidate apar centerlines. The extensions of the reference and candidate apar centerline to their intersection point forms the interconnection.
 - * Collinear case: Connect the reference apar endpoint to the candidate apar endpoint.
 - If the connection type is collinear, then mark the reference endpoint and candidate endpoint as used. If the connection type is normal or perpendicular, then mark only the reference endpoint as used. Multiple collinear type connections are not allowed, but multiple perpendicular type or normal type connections are.
- 4. If any collinear type connections were made, then do step 3 again. Stop when no more collinear type connections were made as a result of step 3 (the only parameter that changes is the length of the apar if a connection was made. By updating the length of the apar, it is hoped to include more global information).

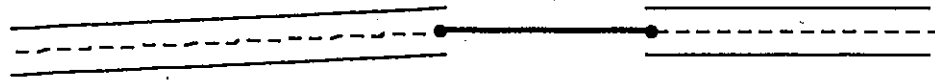
4.3.3 Comments on The Algorithm

A major criticism of the algorithm is its dependence on the order of processing the apars. The reference apars are chosen in random order from the field of potential apars. Potential apars are the bright apars. The reference apars could have been examined in an order imposed by the apar's significance. The longer the length of the apar, the more significant (i.e. highly more likely to be a road type feature) the apar. The choice of which reference apar to consider first is random.

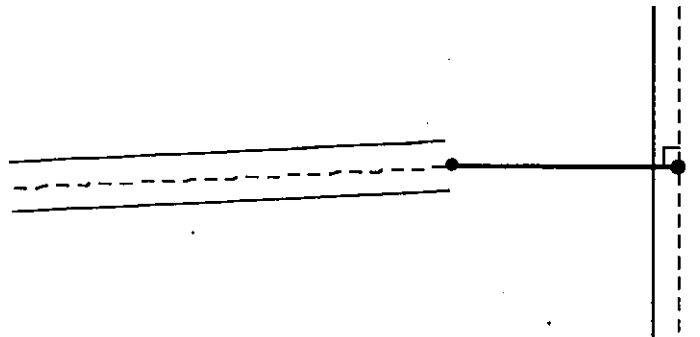
The problem of connecting apars together is based on choosing the best candidate from possibly, many potential candidates. The candidates are ordered with respect to their length. The more significant (i.e. longer) candidates are examined first. The length of the apar does not necessarily mean that it is the proper choice, but rather that it is more likely to be a better candidate than a shorter apar.

The order in which reference and candidate apars are chosen may possibly cause local winners but not necessarily global winners. It is hoped that incorrect local winners are prevented by the spectral constraints and the gap collinearity constraint. Global winners are only possible if they are not inhibited by local winners. Certain connections may inhibit other connections (i.e. a restriction on collinear type connections may prevent the proper connection if an incorrect connection was made).

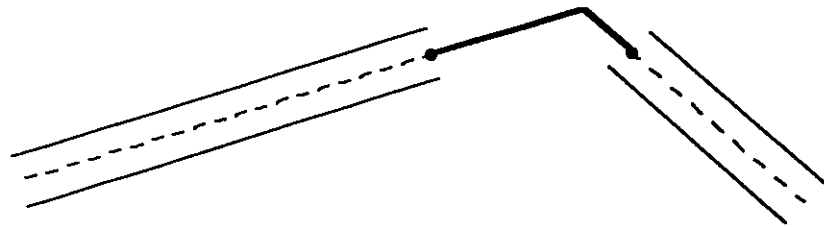
TYPES OF APAR CONNECTIONS



A. COLLINEAR



B. NORMAL



C. PERPENDICULAR

Figure 4.1: Types of Apar Intersections

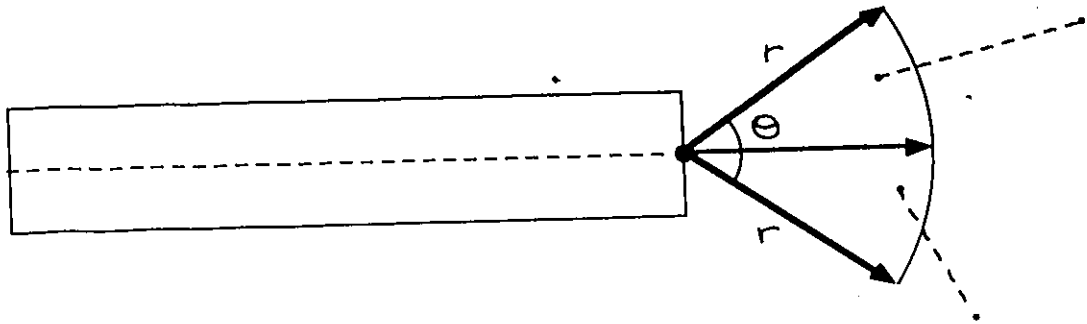


Figure 4.2: The Search for Potential Candidates

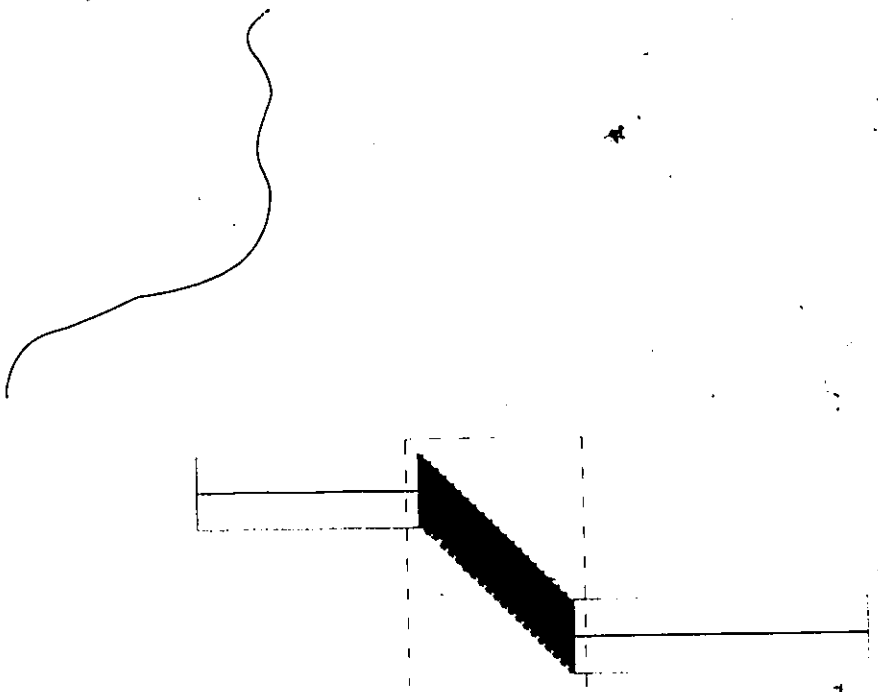


Figure 4.3: Gap Region Between Two Apars

Chapter 5

Results

5.1 Preliminaries

The following figures present the different stages involved in the processing of the input imagery before running the apar connectivity algorithm. Figures 5.1 through to 5.6 show the steps involved for a SPOT PLA image of the Madelaine Islands, Quebec to be transformed from the input imagery to the cleaned apars. Figure 5.1 is the SPOT PLA image. Figure 5.3 shows, as a graphics overlay, the edges which were extracted by the edge extraction process. Figure 5.4 shows the linears which were combined into apar structures, while Figure 5.5 shows the corresponding apar centerlines. Figure 5.6 illustrates the apar centerlines which were kept after removing the redundant apars and grouping apars that share a common side.

Figure 5.7 is a SPOT PLA image of Sherbrooke, Quebec, while Figure 5.8 shows the extracted apar centerlines after the cleaning process.

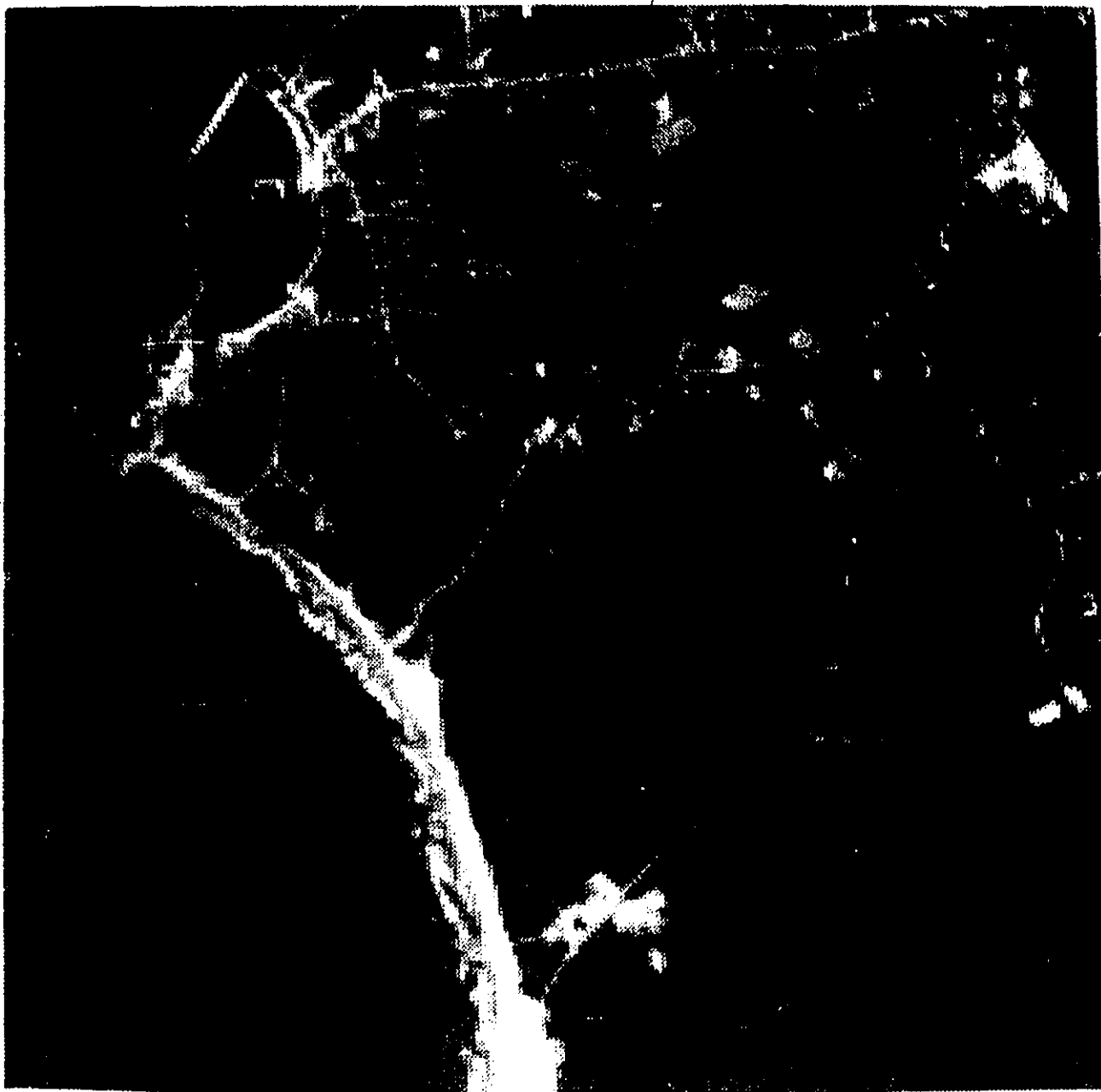


Figure 5.1: Madelaine Islands SPOT PLA: Input imagery. Long parallel linears (apars) are visible in this image. The analysis requires the knowledge of what a road is.

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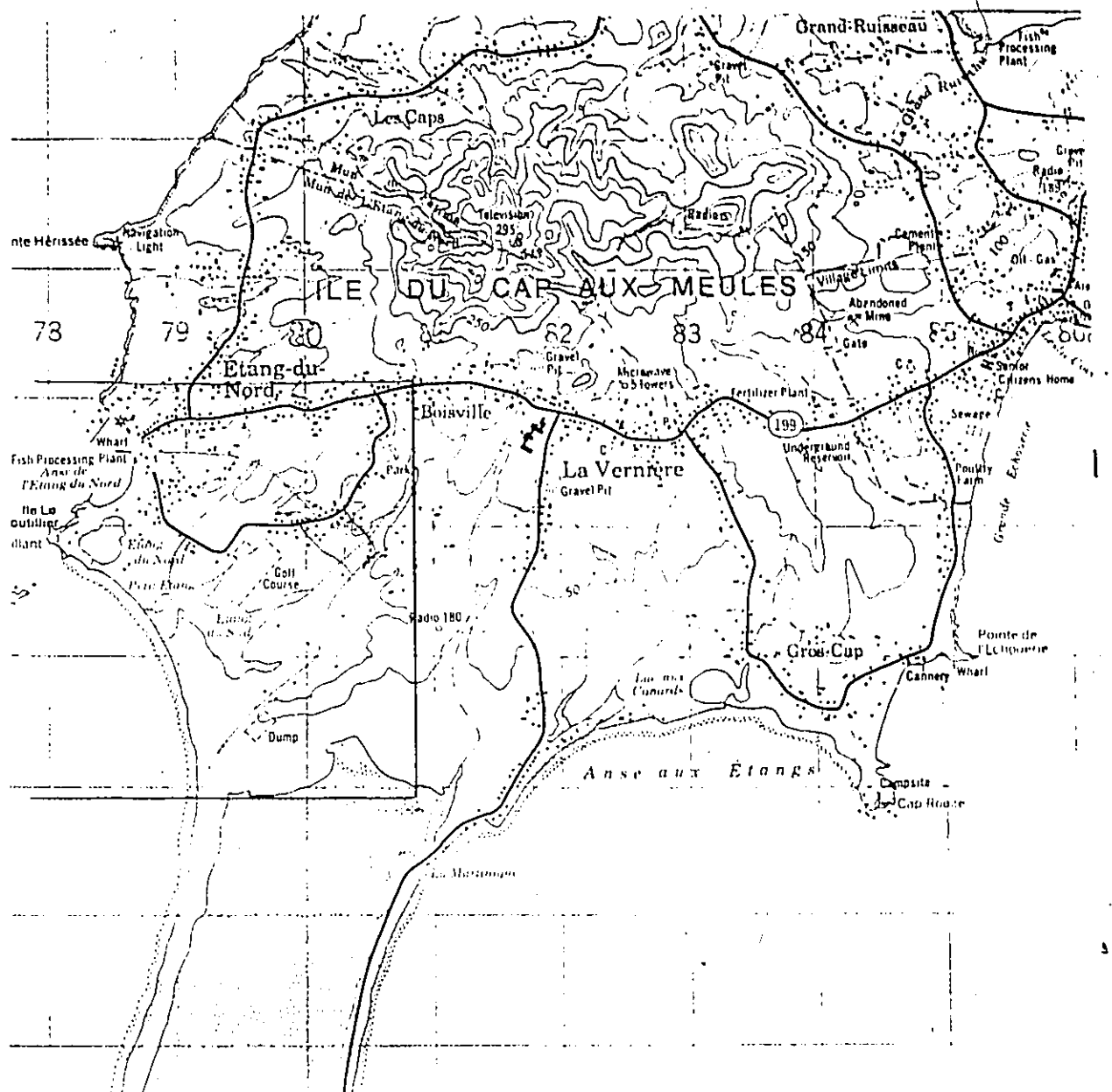


Figure 5.2: Madelaine Islands 1:50 000 Map: Used as a reference to verify which narrow linears are roads. The area of interest which corresponds to the imagery is outlined.

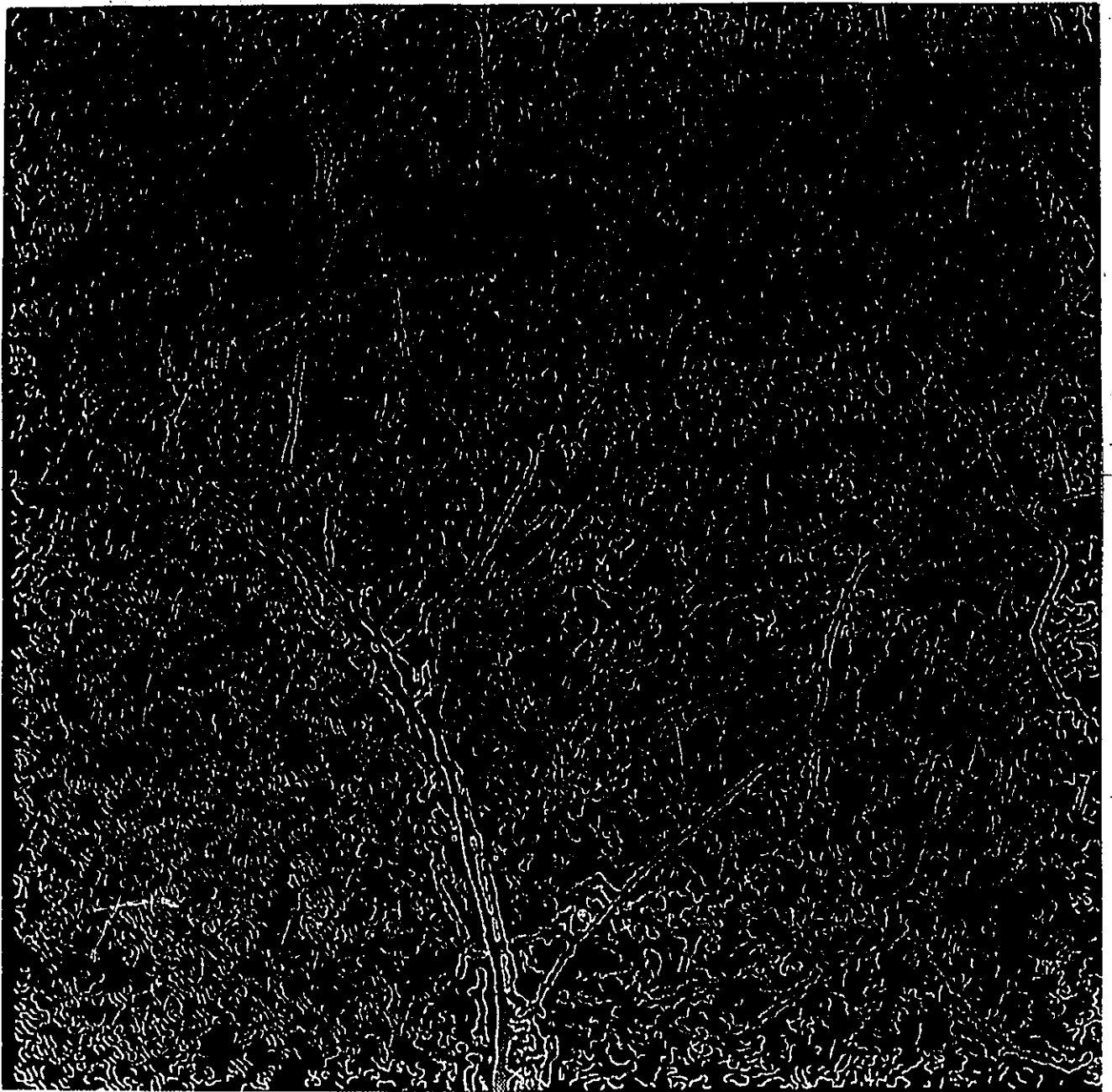


Figure 5.3: **Madelaine Islands Extracted Edges:** The graphic overlay illustrates the edges that were extracted by convolving the image with a DOG filter with sigma values equal to 1.0 and to 1.5. A pattern of long narrow linears is evident.

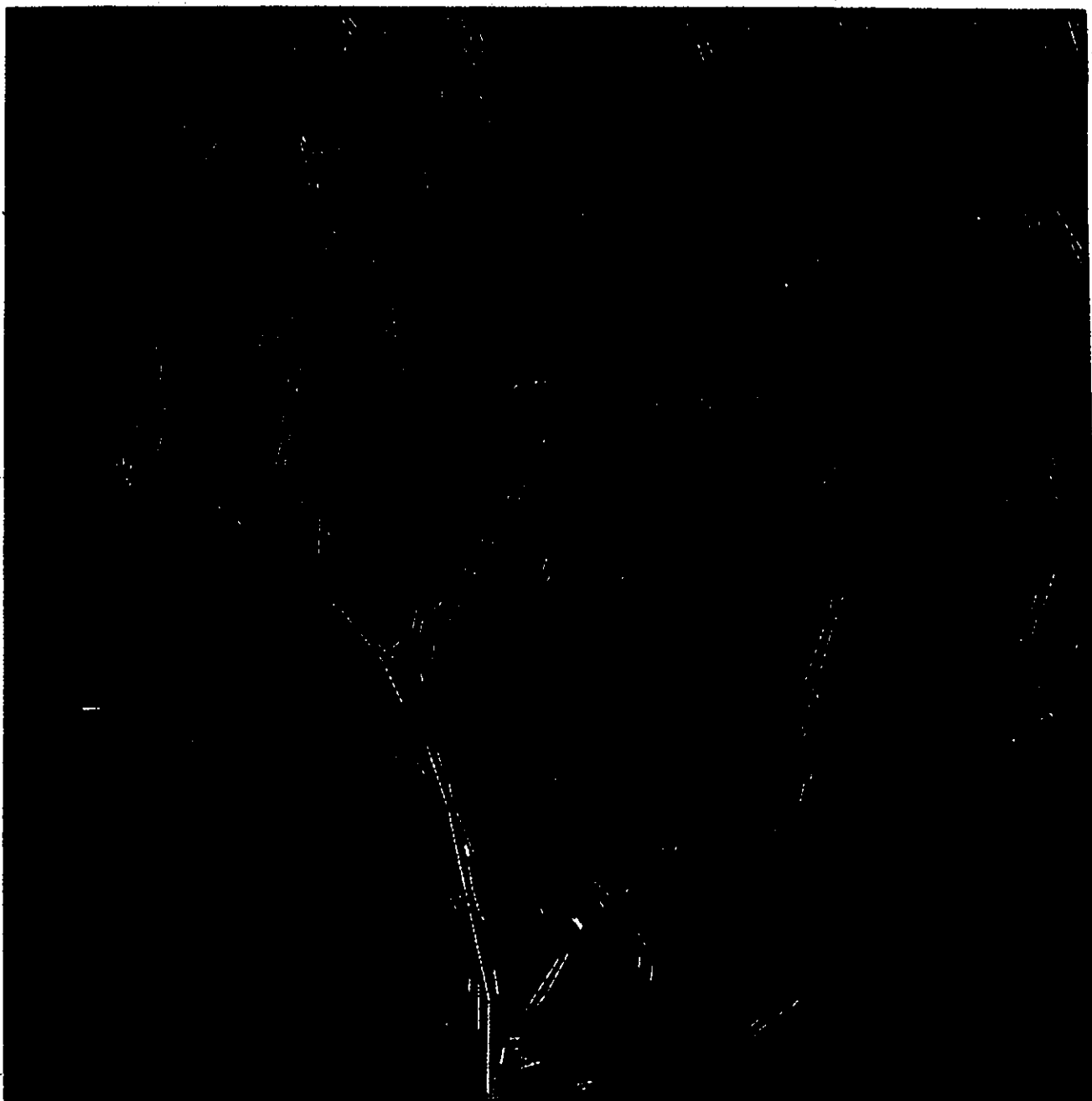


Figure 5.4: **Madelaine Islands Extracted Apar Linears:** The graphic overlay illustrates the linears which were used in order to create apar structures. The apar structures are disjoint by construction.

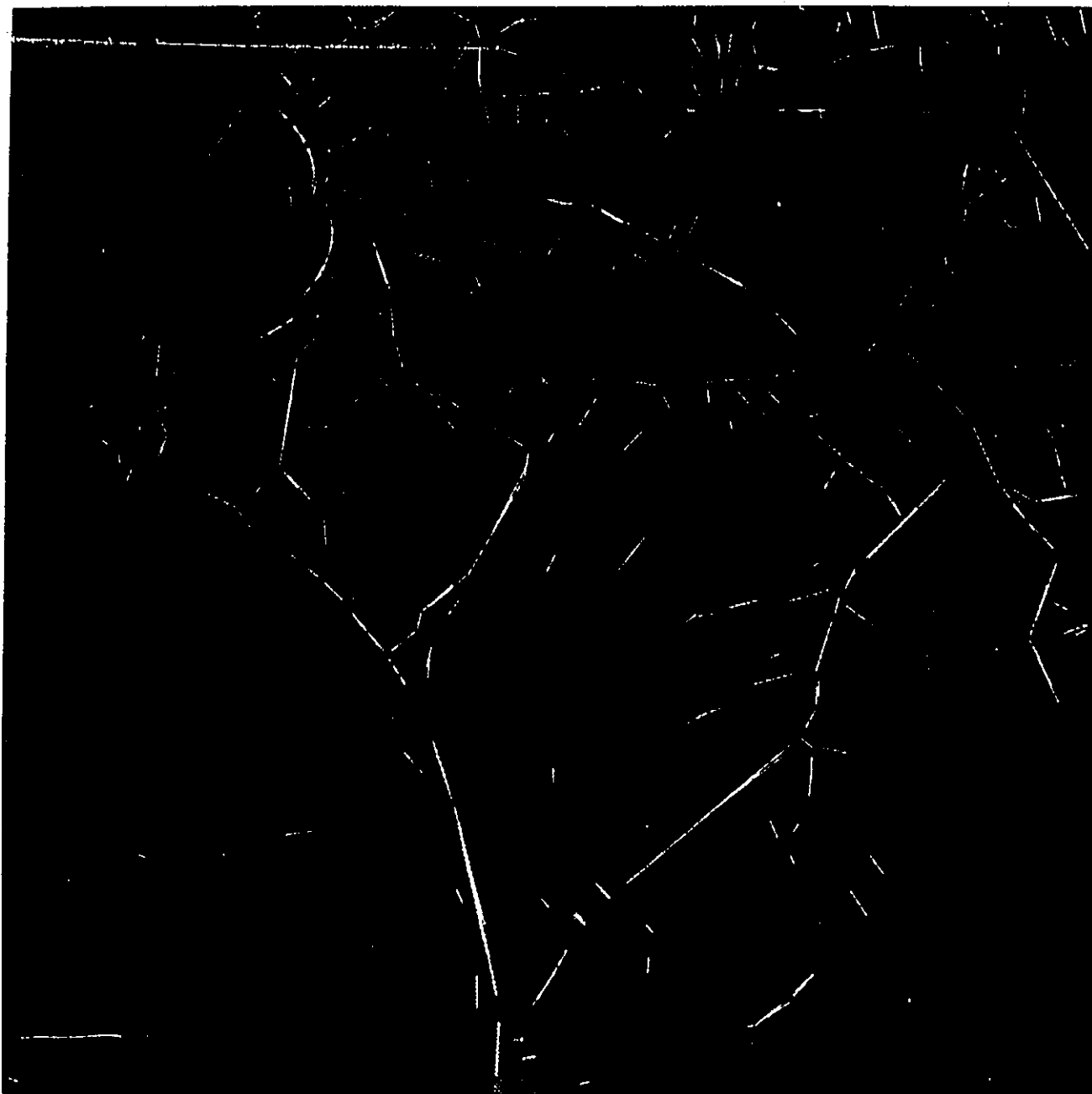


Figure 5.5: Madélaine Islands Apar Centerlines: The graphic overlay illustrates the apar centerlines. Note that prior to cleaning, the centerlines can overlap each other.

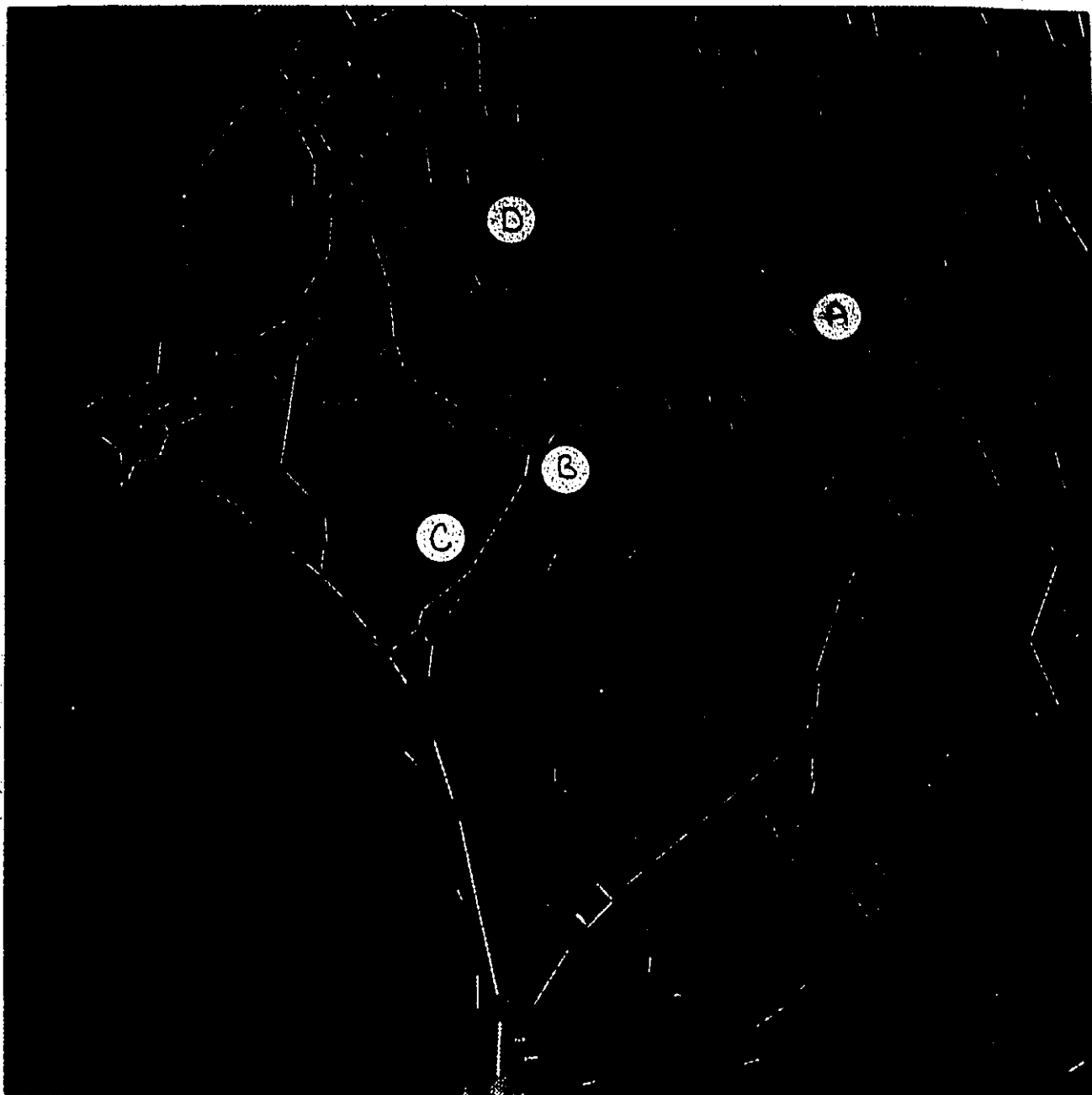


Figure 5.6: Madelaine Islands Apar Centerlines After Cleaning: The graphic overlay illustrates the apar centerlines after removing redundant apars and grouping apars that share a common side. Compared to Figure 5.5, the cleaned version is easier to work with and can possibly be used as a guide for manual digitization. A and B show cases where it would be desirable to search beyond 20 pixels for possible connections. C and D show cases where a smaller search region can be used.



Figure 5.7: Sherbrooke SPOT PLÅ: Input imagery. (This scene involves farm land. There are instances where the spectral reflectivity of the road is similar to the farm field.

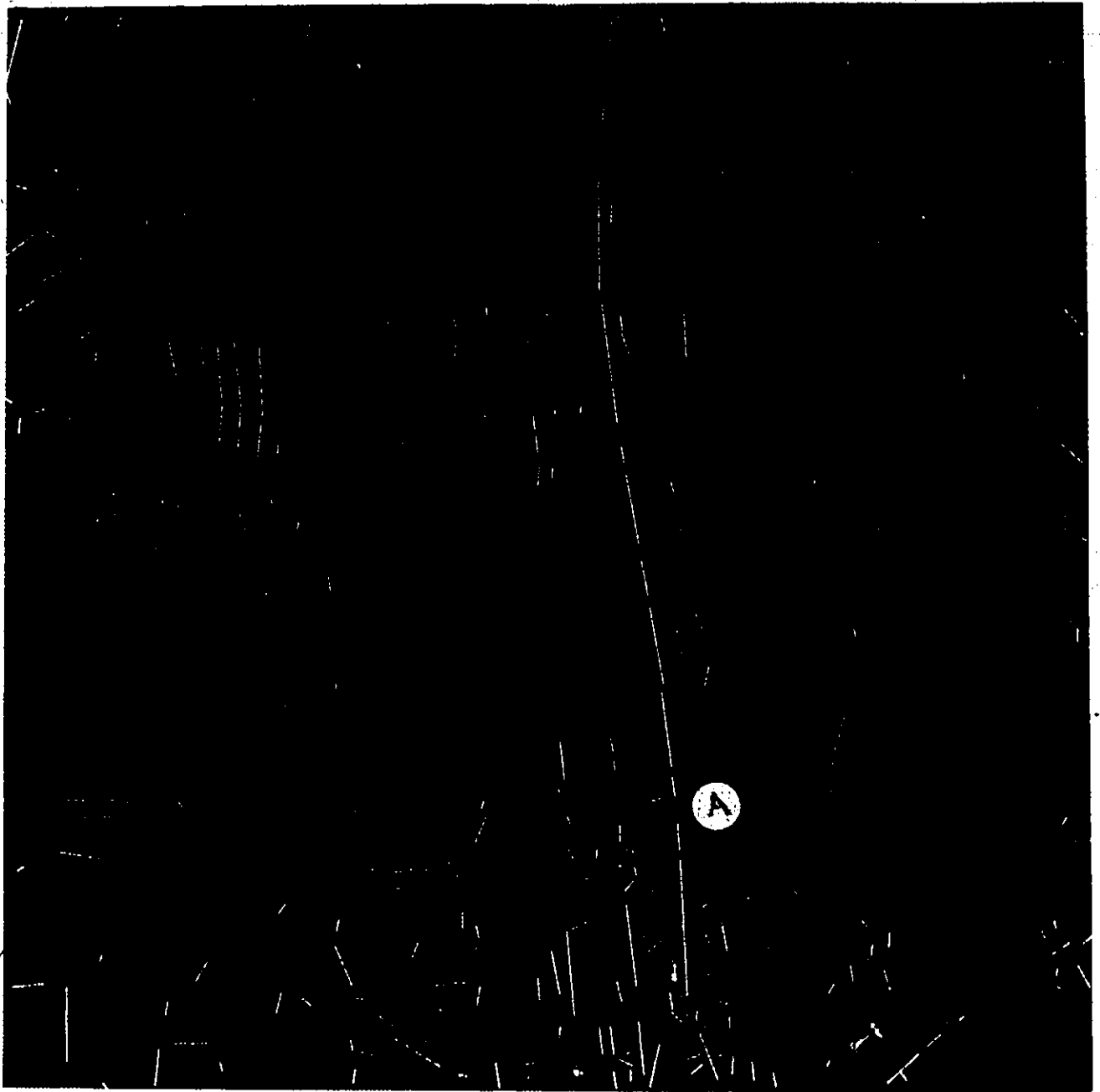


Figure 5.8: **Sherbrooke Apar Centerlines After Cleaning:** The graphic overlay illustrates the extracted apar centerlines after removing redundant apars and grouping apars that share a common side. **A** illustrates where iteration in the grouping algorithm is required: the gap collinearity constraint would prevent this connection; however, a subsequent pass with updated apar lengths would cause the constraints to succeed.

5.2 Algorithm Results

The algorithm was applied to portions of SPOT PLA images that were 512 pixels by 512 lines. The input to the algorithm was the detected apars, the apars deduced from the detected apars (after the cleaning process) and the associated attributes of the real and deduced apars. The threshold value used for the gap collinearity constraint was 1.0. The spectral constraints used a value of 1.0 for the constant k .

The following figures show the final output (existing apars plus connections made) after applying the apar detection and joining algorithm to the SPOT PLA image of the Madelaine Islands, Quebec and the SPOT PLA image of Sherbrooke, Quebec.

The joining algorithm took 26.7 cpu minutes on a μ VAX to run on a 512 chip¹ of the Madelaine Island scene (see Figure 5.13). The joining algorithm took 31.3 cpu minutes to run on a 512 chip of the Sherbrooke scene (see Figure 5.18). A different Sherbrooke scene required 80 cpu minutes (see Figure 5.23). The factors which affect the execution time relate to the number of apars present and the local densities of apars present.

¹ A chip refers to a square (same number of pixels as lines) subscene extracted from an image.

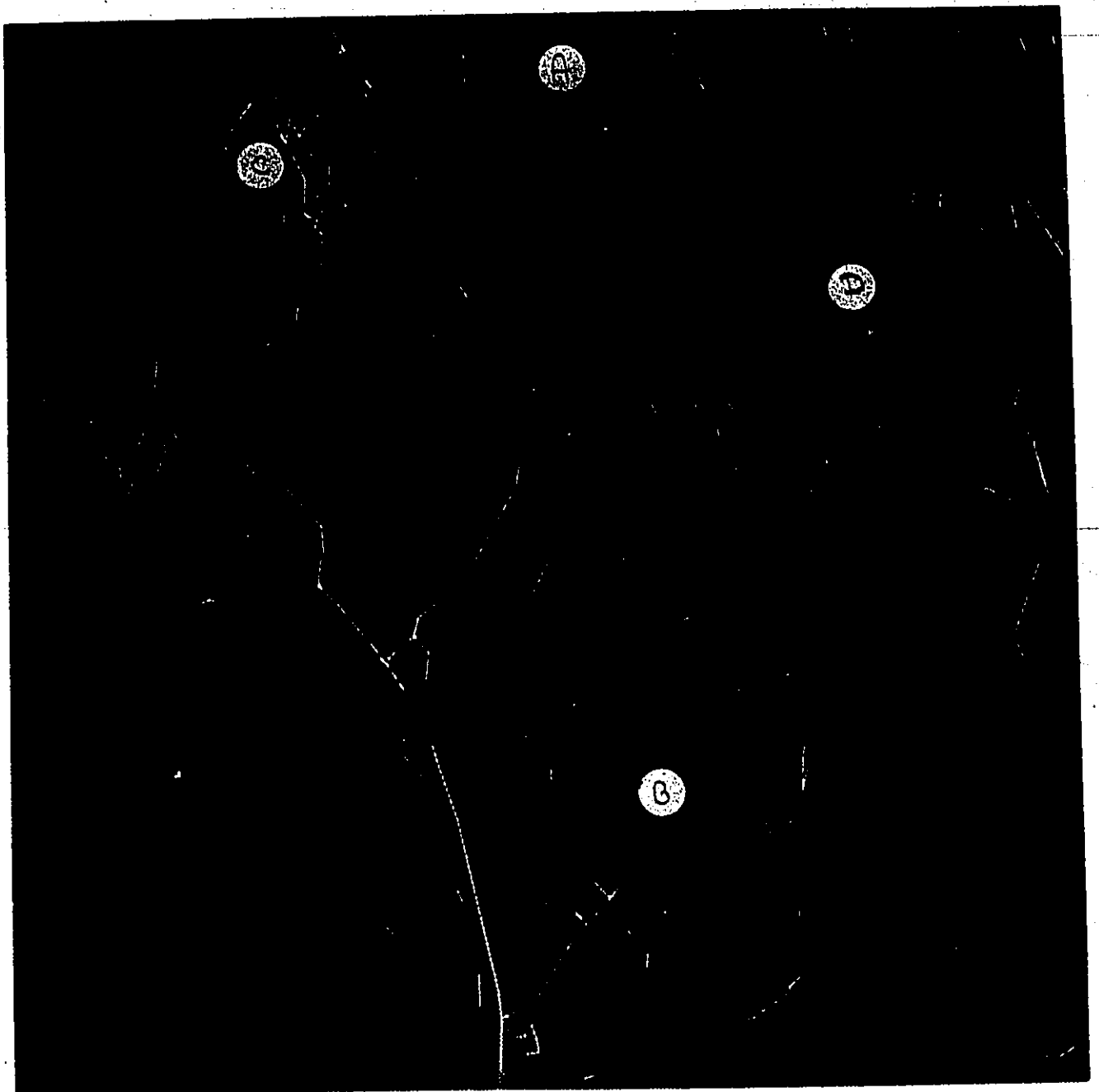


Figure 5.9: Madelaine Islands: Simple Attempt At Connecting Apars: The overlay graphics illustrate the apars with the connections that were made. The only constraint used was the gap collinearity constraint. The candidate which minimized the gap collinearity constraint was chosen. There was no distinctions made about the type of intersection which existed at the connection. All connections were made between apar endpoints. Collinear connections at A and B were made correctly. Perpendicular connections at C and D were not made properly because only endpoints were connected.

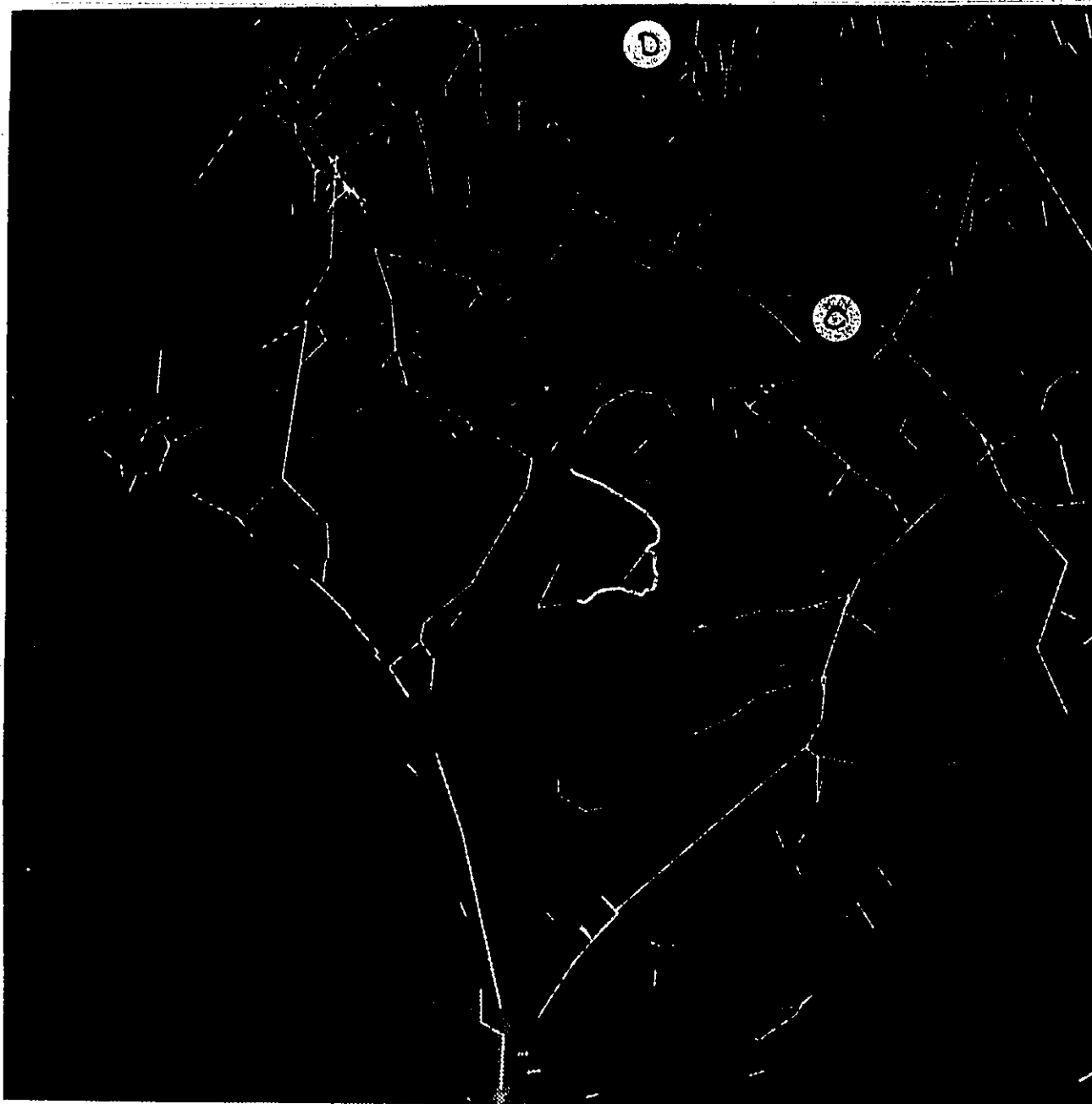


Figure 5.10: **Madelaine Islands: Algorithm Results:** The overlay graphics illustrate the apars with the connections that were made. The joining algorithm determines the type of connection to be made and also uses the spectral statistics to verify if the connection should be made. The analysis of where the algorithm works well and it's weaknesses are discussed in the Analysis section. **D** shows where the connection between apars was made on a subsequent pass. **C** shows where iteration would not help in making this connection, since the search space for potential candidates is too small and the proper candidate wouldn't be considered.

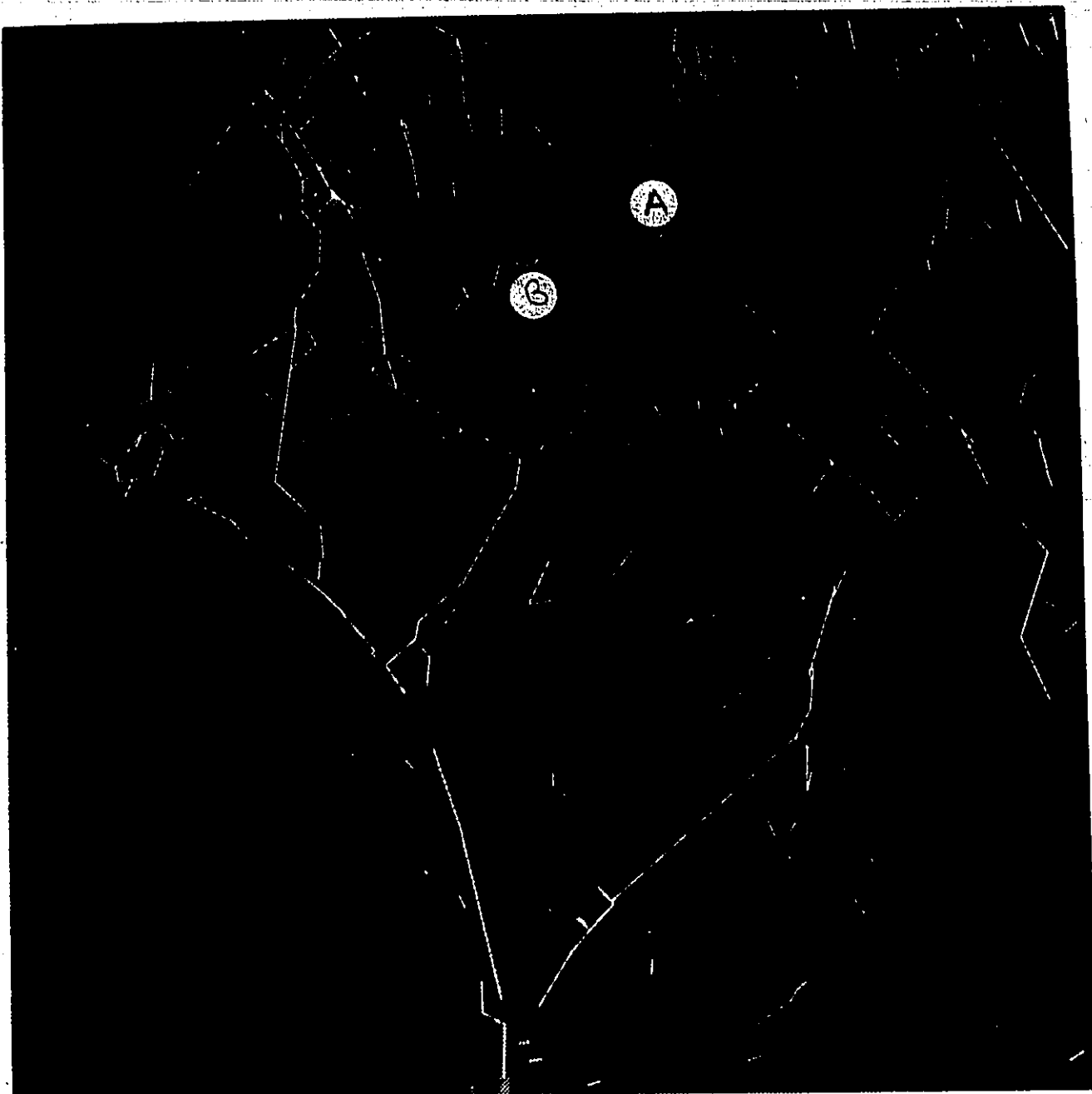


Figure 5.11: Madelaine Islands: Algorithm Results (No Upper Spectral Bound): The overlay graphics illustrate the apars with the connections that were made. The only modification made to the algorithm which produced the results in Figure 5.10 was that the upper bound on the spectral constraint test was removed. By relaxing the spectral constraints, it was hoped to connect apars just because they are bright, and that the gap region between the two apars is bright. Relaxing the constraints in such a manner did not have a major effect. Some additional erroneous connections (A and B) were made as a result of relaxing the spectral constraints.

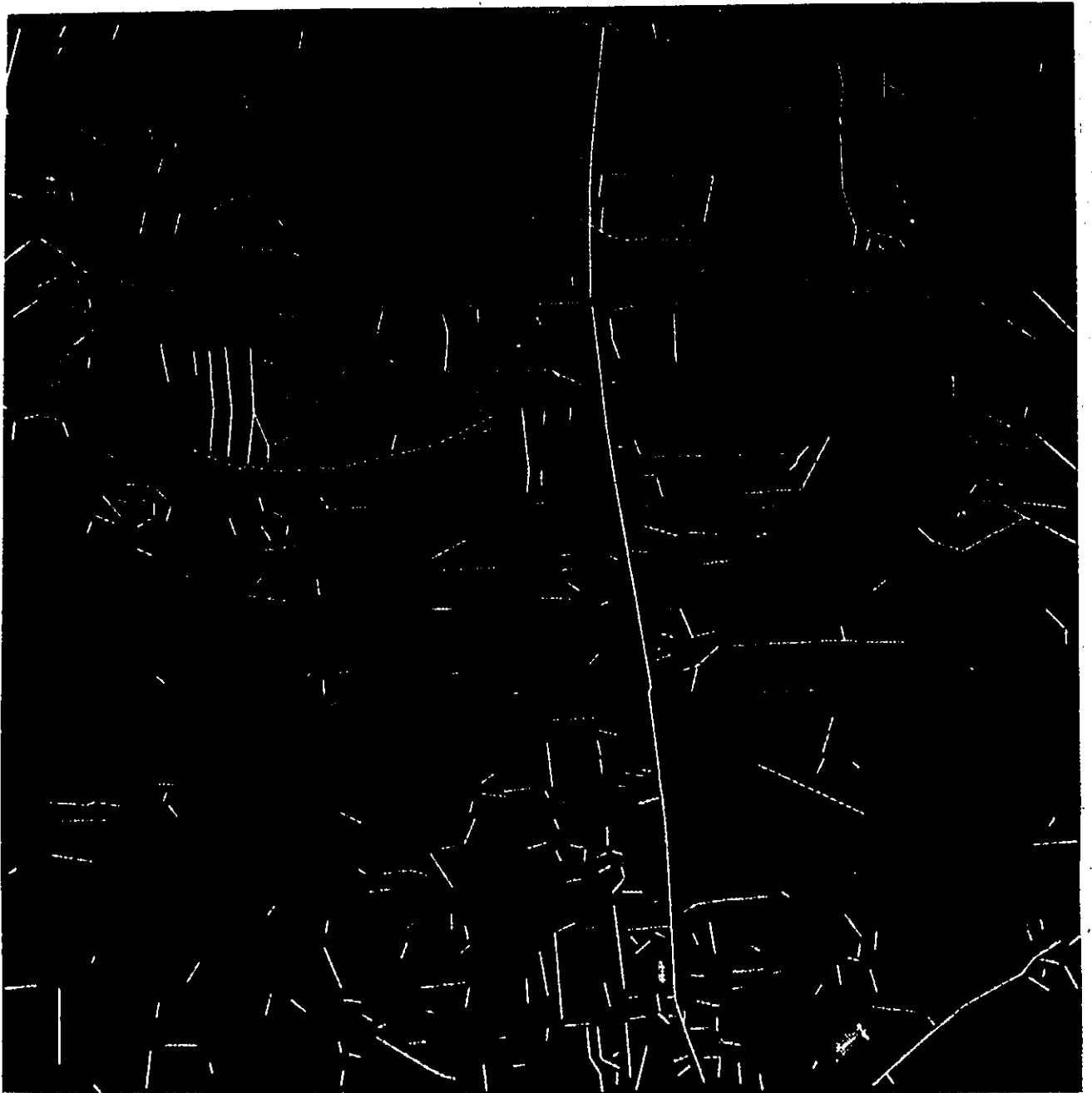


Figure 5.12: Sherbrooke: Algorithm Results: The overlay graphics illustrate the apars with the connections that were made.

5.2.1 Iteration and Constraint Satisfaction

5.2.2 Tests Conducted

The following tests were conducted:

- The algorithm was applied to a SPOT PLA image of the Madelaine Islands, Quebec. The algorithm iterated 3 times until no new collinear connections were found. Tables 5.1, 5.2, 5.3 summarize the number of times in which the constraints succeeded and failed for the three iterations. Table 5.4 summarizes the different types of connections which were made during each of the iterations.
- A modified version of the algorithm was applied to the same SPOT PLA image from the Madelaine Islands, Quebec. The modification was the removal of the upper bound on the spectral constraints (i.e. the right hand side of inequalities 4.1, 4.2, 4.3, 4.4 was removed). Tables 5.5, 5.6, 5.7 summarize the constraints which succeeded and failed for each iteration. Table 5.8 summarizes the different types of connections which were made during each of the iterations.
- Tables 5.9 and 5.10 summarize the constraints' success and fail rate for a SPOT PLA scene from Sherbrooke, Quebec. Table 5.11 summarizes the different types of connections which were made during each of the iterations.

Effect Of Iteration

Most of the connections were made in the first pass (see Tables 5.4, 5.8 and 5.11). This shows that the quantity of connections gained by iteration is minimal, but the quality of connections justifies the iteration process. A in figure 5.8 and D in figure 5.10 illustrate where a connection was made in a subsequent pass. The connection would not have been possible had there been no iteration. The gap collinearity constraint fails on the first pass but succeeds on the second pass because connections made on the first pass caused neighbouring apar lengths to be increased. C in figure 5.10 shows where iteration doesn't help in making a connection, which is a result of the confined search space for potential candidates. The proper candidate is greater than 20 pixels away from the reference apar and therefore never considered.

Iteration	1	1
Test	True	False
Gap Collinearity Constraint	168	92
Apar Spectral Compatibility Constraint	146	22
Gap Spectral Compatibility Constraint	113	33

Table 5.1: Madelaine Islands: First Iteration. Constraints Applied

Iteration	2	2
Test	True	False
Gap Collinearity Constraint	18	72
Apar Spectral Compatibility Constraint	4	14
Gap Spectral Compatibility Constraint	2	2

Table 5.2: Madelaine Islands: Second Iteration. Constraints Applied

Iteration	3	3
Test	True	False
Gap Collinearity Constraint	14	73
Apar Spectral Compatibility Constraint	0	14
Gap Spectral Compatibility Constraint	0	0

Table 5.3: Madelaine Islands: Third Iteration. Constraints Applied

Iteration	1	2	3
Type of Connection	Number	Number	Number
Collinear	61	4	0
Normal	19	0	0
Perpendicular	66	40	0
Total	146	4	0

Table 5.4: Madelaine Islands: 3 Iterations. Connections made

Iteration	1	1
Test	True	False
Gap Collinearity Constraint	161	85
Apar Spectral Compatibility Constraint	161	0
Gap Spectral Compatibility Constraint	161	0

Table 5.5: Madelaine Islands: First Iteration. Constraints Applied. (no upper bound spectral constraint)

Iteration	2	2
Test	True	False
Gap Collinearity Constraint	3	71
Apar Spectral Compatibility Constraint	3	0
Gap Spectral Compatibility Constraint	3	0

Table 5.6: Madelaine Islands: Second Iteration. Constraints Applied (no upper bound spectral constraint)

Iteration	3	3
Test	True	False
Gap Collinearity Constraint	0	71
Apar Spectral Compatibility Constraint	0	0
Gap Spectral Compatibility Constraint	0	0

Table 5.7: Madelaine Islands: Third Iteration. Constraints Applied (no upper bound spectral constraint)

Iteration	1	2	3
Type of Connection	Number	Number	Number
Collinear	61	4	0
Normal	19	0	0
Perpendicular	66	40	0
Total	146	4	0

Table 5.8: Madelaine Islands: 3 Iterations. Connections made (no upper bound spectral constraint)

Iteration	1	1
Test	True	False
Gap Collinearity Constraint	171	217
Apar Spectral Compatibility Constraint	165	6
Gap Spectral Compatibility Constraint	155	10

Table 5.9: Sherbrooke: First Iteration. Constraints Applied

Iteration	2	2
Test	True	False
Gap Collinearity Constraint	7	197
Apar Spectral Compatibility Constraint	0	7
Gap Spectral Compatibility Constraint	0	0

Table 5.10: Sherbrooke: Second Iteration. Constraints Applied

Iteration	1	2
Type of Connection	Number	Number
Collinear	59	0
Normal	27	0
Perpendicular	79	0
Total	165	0

Table 5.11: Sherbrooke: 2 Iterations. Connections made

The connection to candidates is constrained by the search method. Most of the normal type connections are made in the first pass. A normal type connection can be made in subsequent passes if the length of the reference apar has changed due to a connection in a previous iteration.

Effect of Constraints Pruning

Initially, the search space for potential connections is pruned by the search region for candidates. The results indicate that most of the pruning of potential candidates is done by the Gap Collinearity Constraint (see Tables 5.1, 5.2, 5.3, 5.5, 5.6, 5.7, 5.9, 5.10). When the upper spectral bound was taken off the spectral constraints, it was found (as shown by A and B in Figure 5.11) that the spectral constraints did not prune any additional candidates, but rather introduced errors of commission.

5.2.3 Examples of Particular Cases

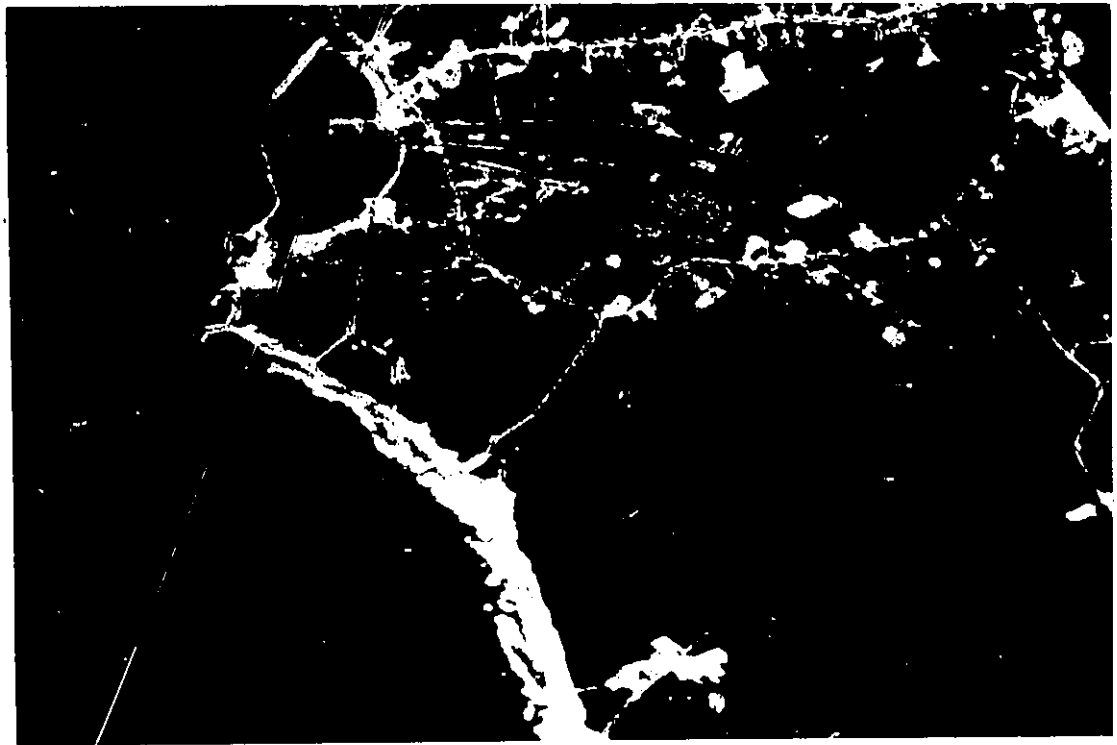


Figure 5.13: Madelaine Islands: Apars & Connectors: The blue graphics are the connections that were made; whereas, the red graphics are the original detected apars.

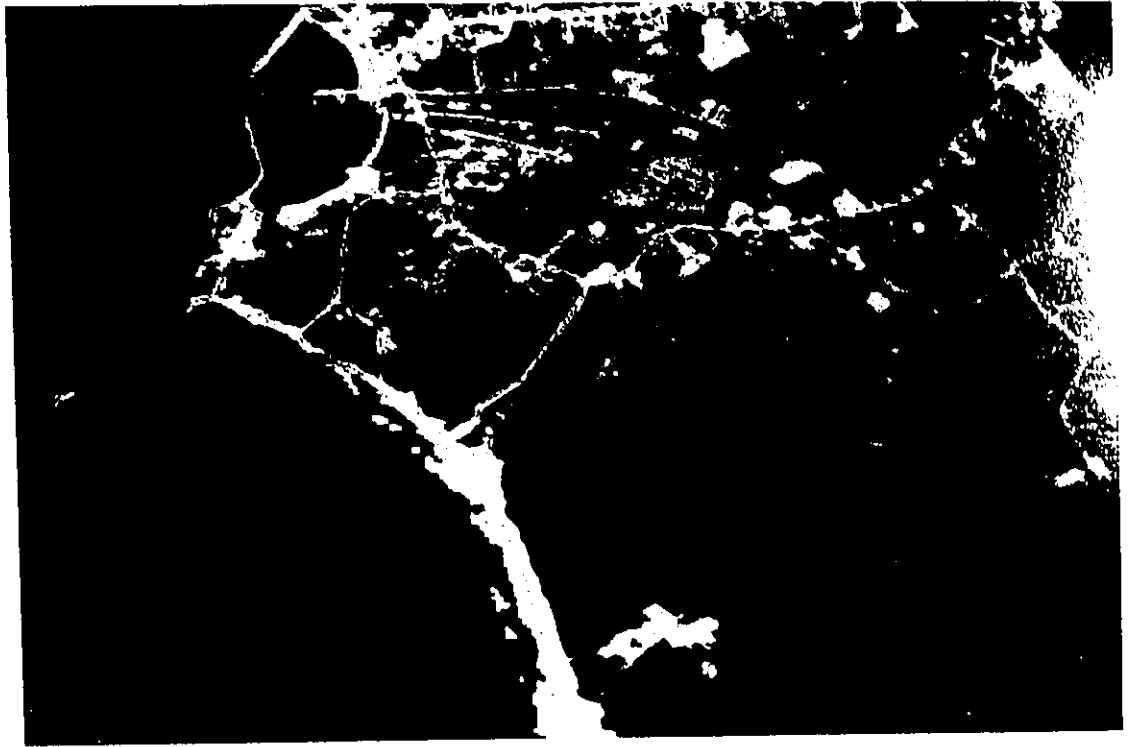


Figure 5.14: **Madelaine Islands: Classified Water:** Shows how contextual information can be used to prune the search space. The blue graphics overlay is obtained by classification thresholding the SPOT MLA3 band (near-infra-red band). It was found that the SPOT MLA3 band has a bimodal histogram distribution.

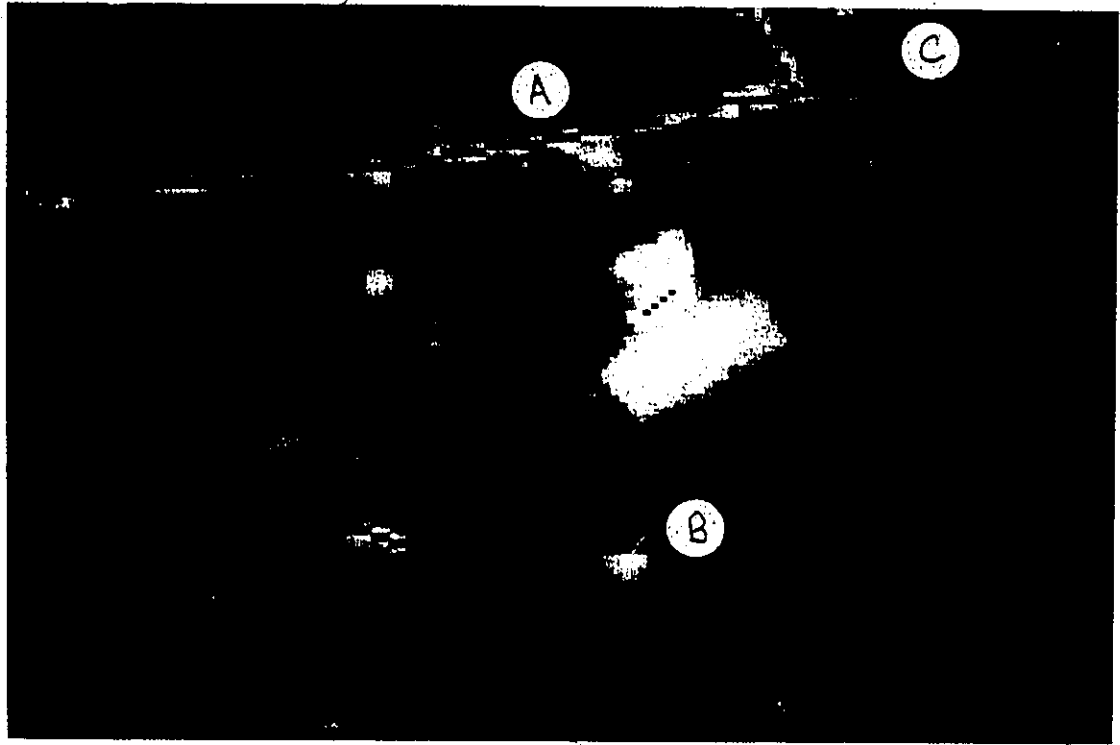


Figure 5.15: Madelaine Islands: Enlargement 1: A shows good collinear connections. B shows an erroneous connection that could have been prevented by adjusting the parameters of the gap spectral similarity constraint. C shows a proper normal type connection. The connection at C is actually two perpendicular type connections.

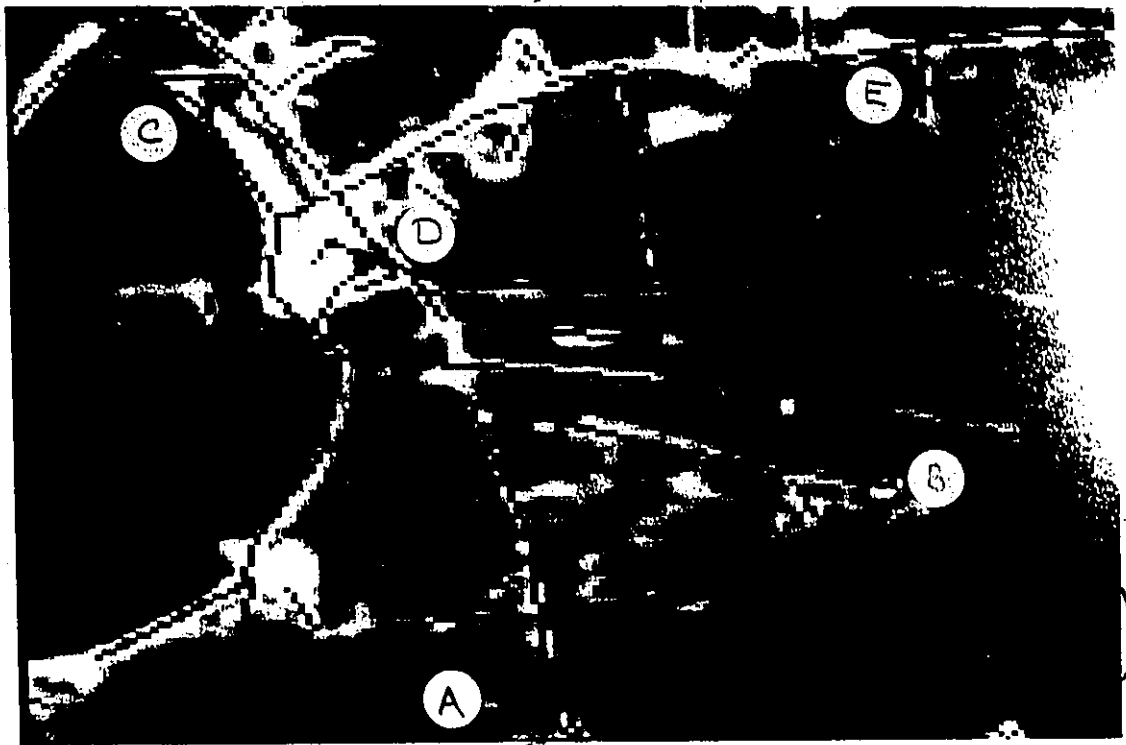


Figure 5.16: Madelaine Islands: Enlargement 2: A and B show connections which should have been rejected by the gap similarity constraint. C shows a bright region where the gap spectral constraint isn't sufficient, but a local edge detection process might properly define the connection. To the left of D, the proper connections were made, but the connections could have been made cleaner. E shows a good collinear type and normal type connection. The gap collinearity constraint rejects the connection to the left of E as the gap collinearity constraint would fall above the 1.0 threshold value.

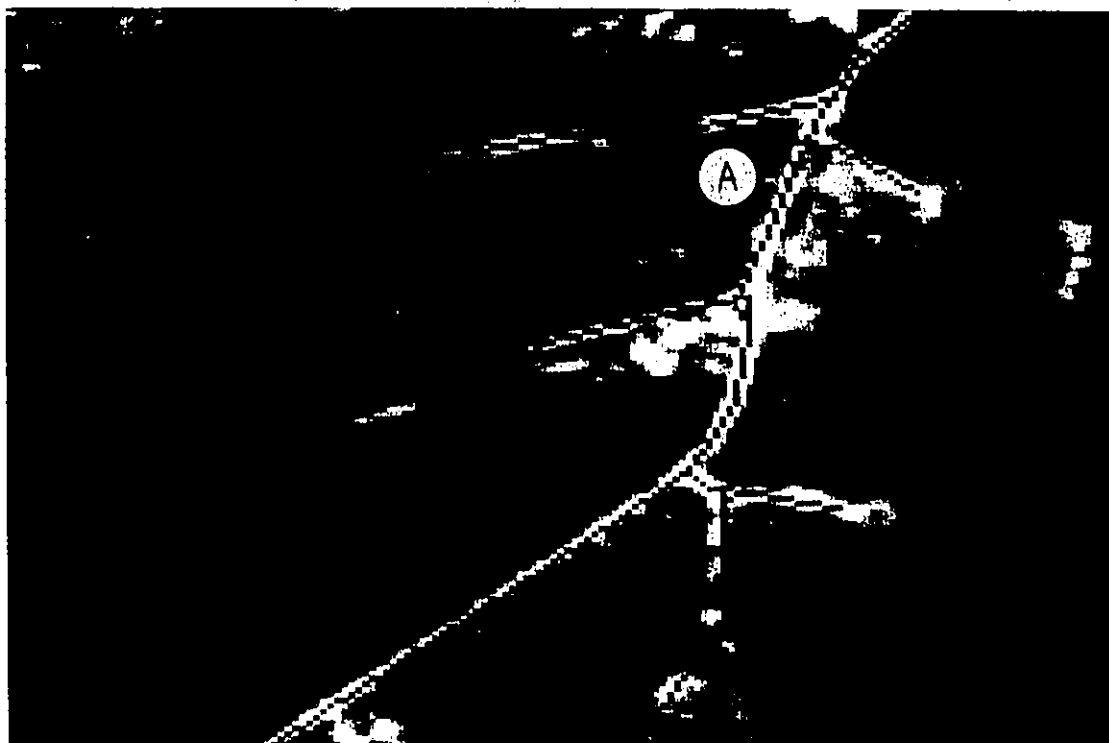


Figure 5.17: Madelaine Islands: Enlargement 3: A shows a normal type connection that was made but should have been rejected by the gap spectral constraint.



Figure 5.18: Sherbrooke (scene 1): Apars & Connectors: The blue graphics are the connections that were made; whereas, the red graphics are the original detected apars.

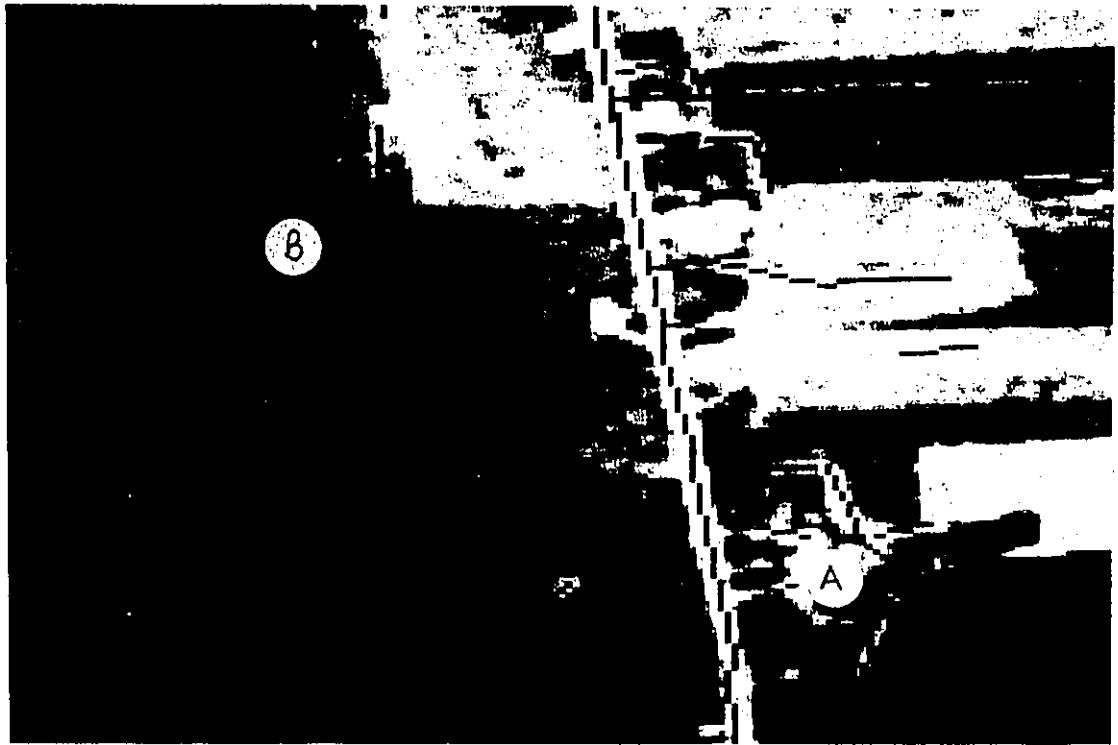


Figure 5.19: Sherbrooke (scene 1): Enlargement 1: A and B show bad connections that were made, due to a wide allowable spectral variance in the gap spectral constraint.

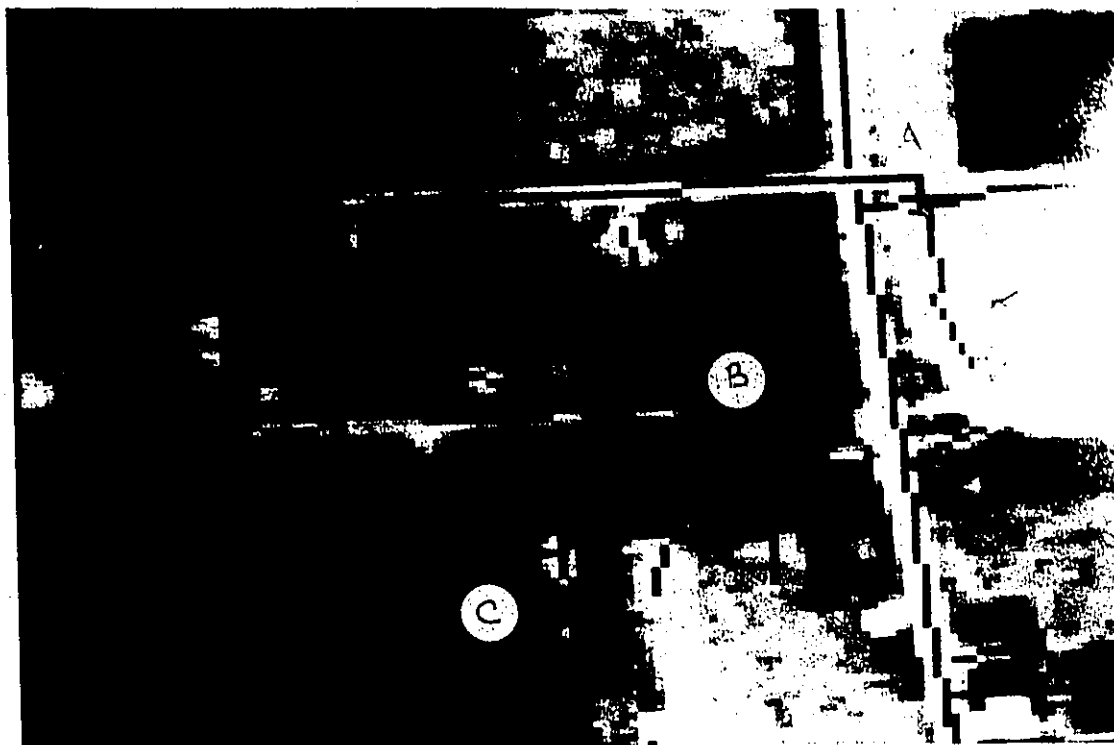


Figure 5.20: Sherbrooke (scene 1): Enlargement 2: The connections around A were made, but could be better arranged if global patterns were used as indicators. The vertical connection at A was missed because the lower vertical apar was too short for the gap collinearity constraint. Connections at B and C should have been rejected by the gap spectral constraint.

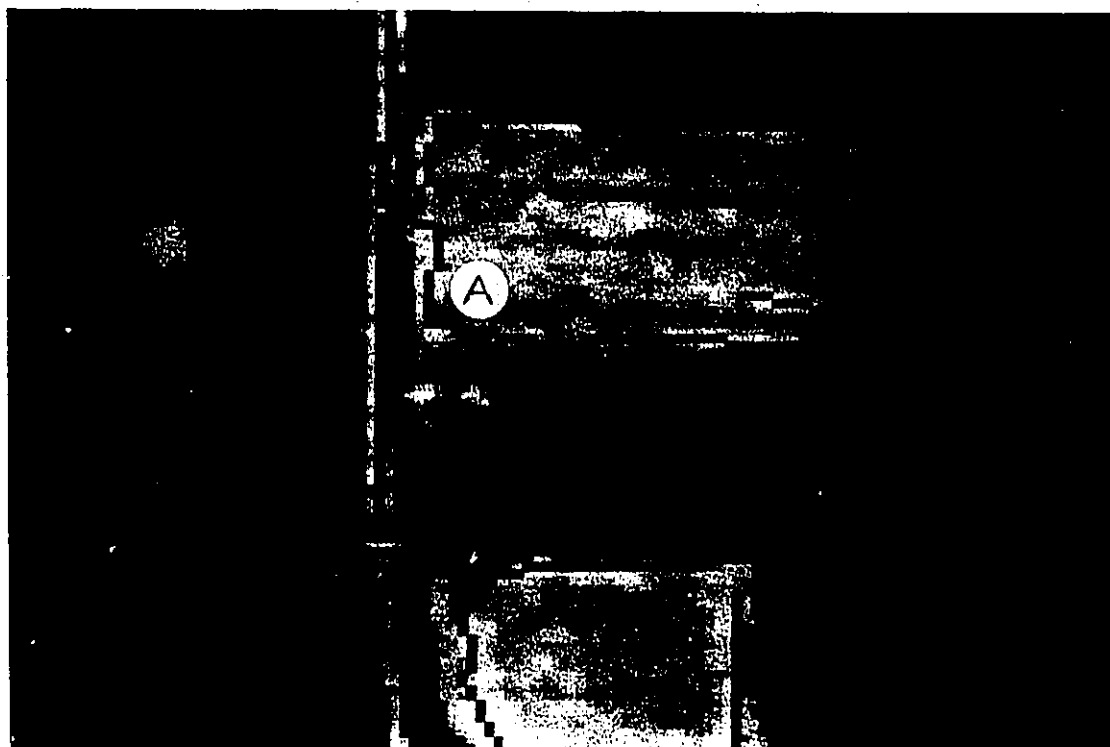


Figure 5.21: Sherbrooke (scene 1): Enlargement 3: In A, the neighbouring region has similar reflectance to the desired narrow linear feature. Gap spectral constraints are useful in these situations to allow connections even if sufficient edge information is missing.



Figure 5.22: Sherbrooke (scene 1): Enlargement 4: A, B, C and D connections should have all been rejected because of the spectral constraints.

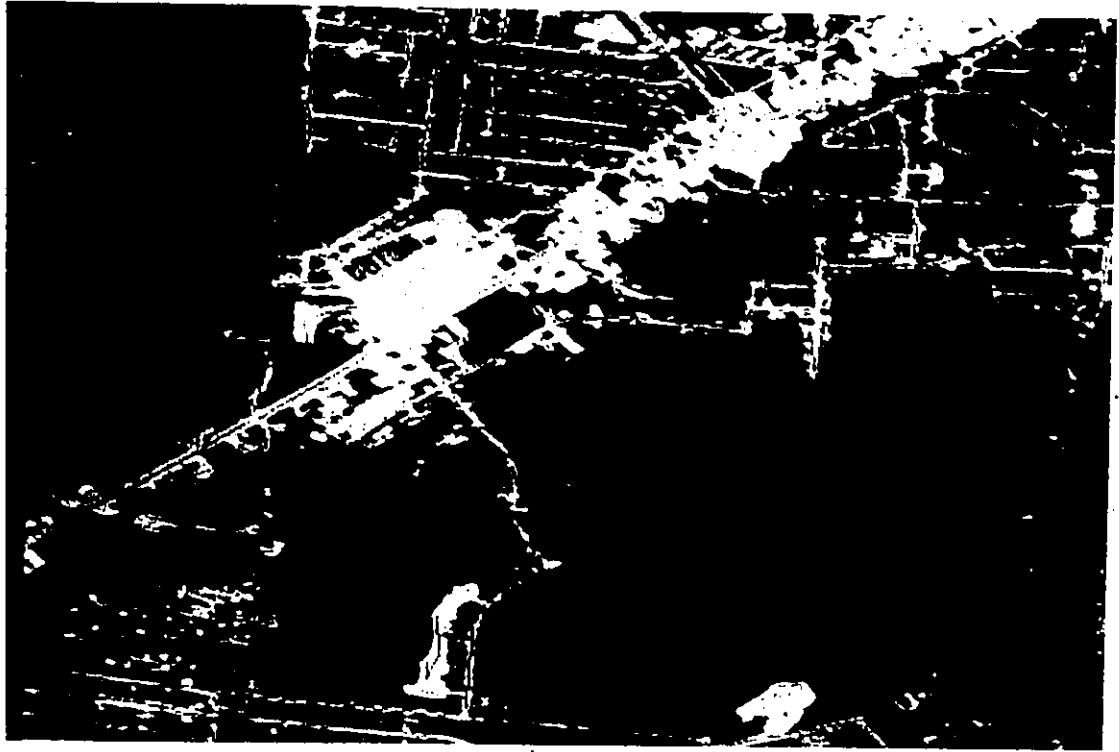


Figure 5.23: Sherbrooke (scene 2): Apars & Connectors: The blue graphics are the connections that were made; whereas, the red graphics are the original detected apars.

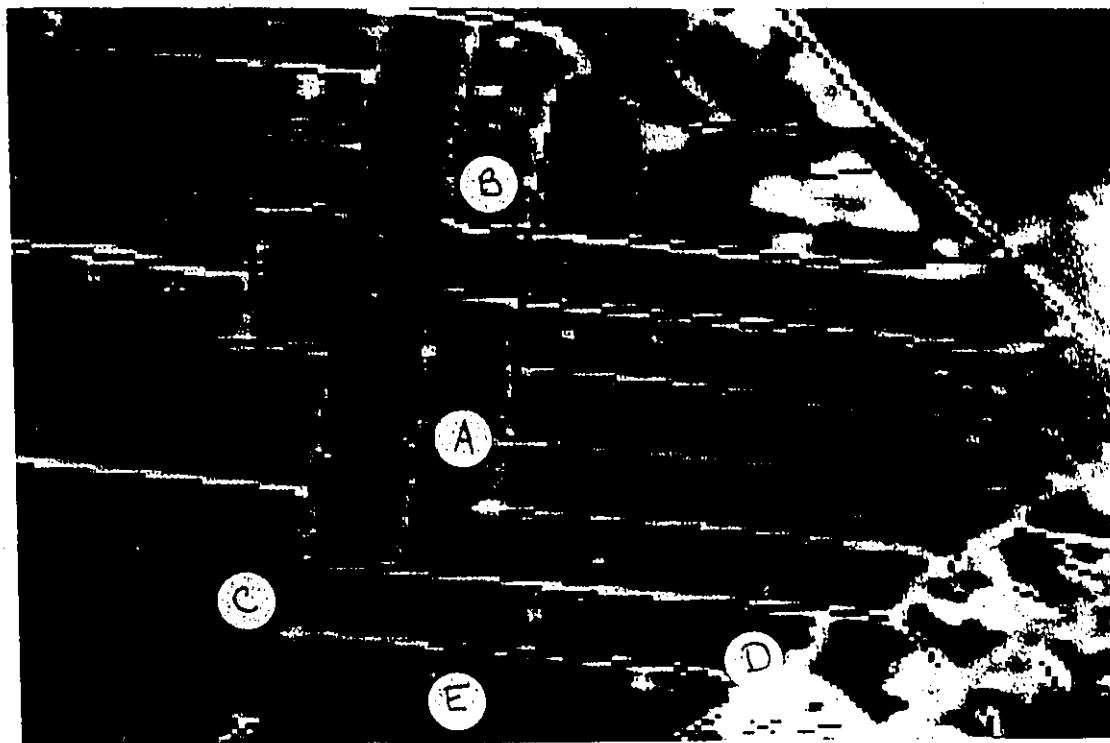


Figure 5.24: Sherbrooke (scene 2): Enlargement 1: This image is a highly dense urban region. In situations such as this, the results are highly dependent on what apar primitives were originally extracted. The possible connection to the right of A was missed because of the gap collinearity constraint (the minimum apar length was too short). B shows a good intersection connection. C shows a bad connection that should have been rejected by the gap spectral constraint. D shows a good collinear connection. The 2 apars to the top of E should have been merged in a cleaning process prior trying to connect them. This shows the dependency of the connectivity analysis on the lower level primitives.

5.3 Analysis of the Algorithm

The results of the algorithm, that interconnects the disjoint apar segments, shows both strengths and weaknesses.

- The **search for potential candidates** is limited to a fixed region around the point of interest. In certain circumstances (A and B in Figure 5.6), it would be desirable to search beyond this predefined region (if a desirable candidate is outside the search region because of a large gap), while in other situations (C and D in Figure 5.6), it would be advantageous to search a much smaller region (for reduction of processing time for small gaps). It may be necessary to grow the search region as required when candidates fail the constraint tests.
- The equation (4.5) used for the **Gap Collinearity Constraint** is subject to some criticism. There is not much argument in using the length of the gap as the numerator. Using the minimum apar length as the denominator is questionable in certain situations. In some situations it would be desirable to have as the denominator, the sum of the two apar lengths, while in other situations, it would be sufficient to have the minimum apar length (as is done now).
- The **Apar Spectral Constraint** is used to check for the spectral similarity of the reference and candidate apar. This constraint can be relaxed in some cases where it doesn't matter that the two apars to be joined are of the same type (i.e. two sections of road, where the road material changes surface cover type (gravel to paved)).
- The **Gap Spectral Constraint** is used to check for the spectral similarity of the gap region in comparison to both of the apars to be joined. In certain situations (Figures 5.15, 5.16 and 5.17), this constraint appears to be too relaxed. The gap spectral constraint only checks for spectral compatibility. This works well if the gap apar has the same spectral properties as compared to the neighbouring regions. If the neighbouring region has the same spectral response as the real-world apar-like feature, then using other edge detection strategies would be futile since there are no real-world edges. Additional information such as edge information could be useful if edges exist in the gap region but were missed by the original edge detection process.

Edge information obtained from another edge detection method would indicate the type of connection if it existed.

- The joining algorithm works well for collinear type connections (see Figure 5.15) in most situations, and normal type and perpendicular type connections (see Figure 5.15) in uncluttered regions. Clutter refers to the number of apars in a certain region which results in ambiguity with respect to which apars to connect. The algorithm is very dependent on the amount of information that was extracted at the lower levels by the edge and apar extraction.
- The joining algorithm has problems when not enough apar information exists (see A in Figure 5.6). The notion of having two different apar types and handling them separately creates problems. The deduced apar candidates are tested before the real apar candidates. Originally it was thought that it didn't matter which apars were tested first (real or deduced). The deduced apars are tested first because they are thought to be more significant (i.e. created by combining apars).

The two groups of apars are sorted with respect to minimizing the Gap Collinearity Constraint. Once a connection is made, the appropriate endpoints are marked as used and are not permitted to be connected with other apars. These constraints affect the connections that are made and missed. The basic control strategy does not attempt to deal with the possibility of an incorrect connection (see Figures 5.16 and 5.17).

Chapter 6

Conclusions and Recommendations

6.1 Conclusions

- The results show that the apars can be connected into larger domain independent primitives. The development of global primitives, such as apar collinear-segments and apar segments, is a start in trying to obtain global information about primitives. Collinear-segments and segments allow easy access of global information; whereas, apars only provide local information.
- The connecting of apars into global primitives was performed with reasonable accuracy. Some incorrect connections were made.
- The larger the gap region, the less accurate the connection model would be. Other low level operators (i.e. other edge detection methods) may allow the accurate definition of the gap region between two apars. The present connection scheme does not take into account the accurate definition of the connection between two apars, but rather tries to determine which apars should be connected.
- The results of connecting apar structures is highly dependent on the results of previous stages. If the gaps are too large, then very few connections will be made. The number of apars detected and their placement is very important in trying to extract global primitives (i.e. collinear-segments). The algorithm used is very sensitive in areas

where there are many apars (i.e. urban areas) and is sometimes not clear on which apars should be connected. The gap spectral constraint did not prune all incorrect choices.

- The algorithm results allow for easier digitization of parallel narrow linear features (i.e. roads), as there are fewer gaps that the user has to bridge (connect). The photointerpreter can connect or reject selected apars as part of a feature of interest.
- Similar principles that are used in connecting narrow linear features may be useful for connecting linear features (i.e. edges). For linear features: rather than looking at the interior spectral statistics, the spectral statistics to the left and to the right of the linear would be used.
- The results of the algorithm are dependent on the order of processing the apars. There are no provisions to undo an incorrect connection. There is a reliance on the constraints to trap for incorrect connections which is not sufficient in all cases. A connection that is locally satisfactory might not necessarily be globally satisfactory.
- The iterative grouping does not buy more connections, but the few connections it does provide are fairly important.

6.2 Recommendations

- Certain improvements can be made to the existing algorithm in order to improve the accuracy. Undoing a connection in certain situations may help in eliminating incorrect connections (i.e. non-monotonic). Experimentation is required with the sensitivity of the spectral constraints in order to determine what parameters and equations are most appropriate. The experimentation with parameters requires the use of a better environment in order to analyze the results. A debugging environment which allows the visualization of spatial primitive relationships would facilitate greater progress in this research area.
- A method of incorporating additional information sources is required (i.e. DEM, other SPOT bands, air photos, existing maps, ...). An example on the use of MIA3 data to incorporate context was shown in Chapter 5.

- A formal definition of the mapping from the primitive dimension to the composition dimension is required. The control strategy that maps primitives into real-world features using declarative rules needs to be defined.
- The method of incorporating other feature knowledge (context) needs to be defined. At what level should context be introduced? Context can be introduced at high levels (i.e. roads are near buildings) or at the lowest level (i.e. use water classification to prune water areas for further land area detection at the edge level). Textural information can allow contextual deductions (i.e. urban texture can dictate a grid-like pattern for roads).
- One of the observations of the thesis work is that global primitives are dependent on the primitives used in their creation. Errors are propagated up the primitive hierarchy. A certain threshold of error is allowed, where above that level, the accuracy of the next higher level would drastically reduce. Research should be conducted into how graceful the degradation of the primitives are with respect to the error level of the primitive children.
- Possible improvements to the joining algorithm may help in achieving the goal of extracting reliable global primitives from apars.
- Other operators can be used to judge the gap region. Presently, the spectral characteristics of the gap region are used as an indicator. Further constraints via other operators can help to minimize incorrect connections. Other edge detection strategies, morphological operators, classifiers and operators dedicated to the image type and resolution can be used to provide additional primitive information.
- Global patterns dictate general trends which may initiate correction of local variations in a collinear-segment. When apars are connected into larger segments, there can be slight perturbations. A mean square error analysis on a collinear-segment can straighten out the slight perturbations.
- Improvements to the spatial indexing strategy and searching routines may reduce the processing time required.

- The global apar-based primitives try to eliminate errors of omission which are present due to the inadequacies of the edge detection and subsequent processing to obtain apar structures. For automated road detection, a more formal organization of the knowledge and reasoning strategy is required.

6.3 In Closing

The apar primitives provide shape information and the associated areal SPOT PLA spectral statistics. Apar primitives were chosen because of their natural association with road features. Apar primitives can be used for other features with other input imagery types. Dark apars can be used as cues for streams and rivers. In higher resolution imagery (i.e. air photos, 1.5 m), apars can be used as cues for features such as ships and cars. Due to the imperfections involved in detecting apars, global primitives will still be required in order to group disjoint apars.

The thesis tackled one issue in the process of trying to automate the extraction of road features from SPOT PLA imagery. The development of global primitives from apar structures results in global information for use in deducing what real-world feature an apar maps into. Apars provide only local information as they are disjoint by nature. Connecting apars together allows deducing information such as global curvature; which may help in making a road distinguishable from a railway line. The results are promising, but a lot of additional research is required in order to achieve the goal of automating the extraction of roads from SPOT PLA imagery.

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Appendix A

Additional Results



Figure A.1: Madelaine Islands SPOT MLA3: The MLA3 band is the near-infra-red band. The histogram of the image has a distinctive bimodal distribution. Water and land can be separated based on thresholding the image. The classification of the water allows one to prune the water areas from the search space for road features.

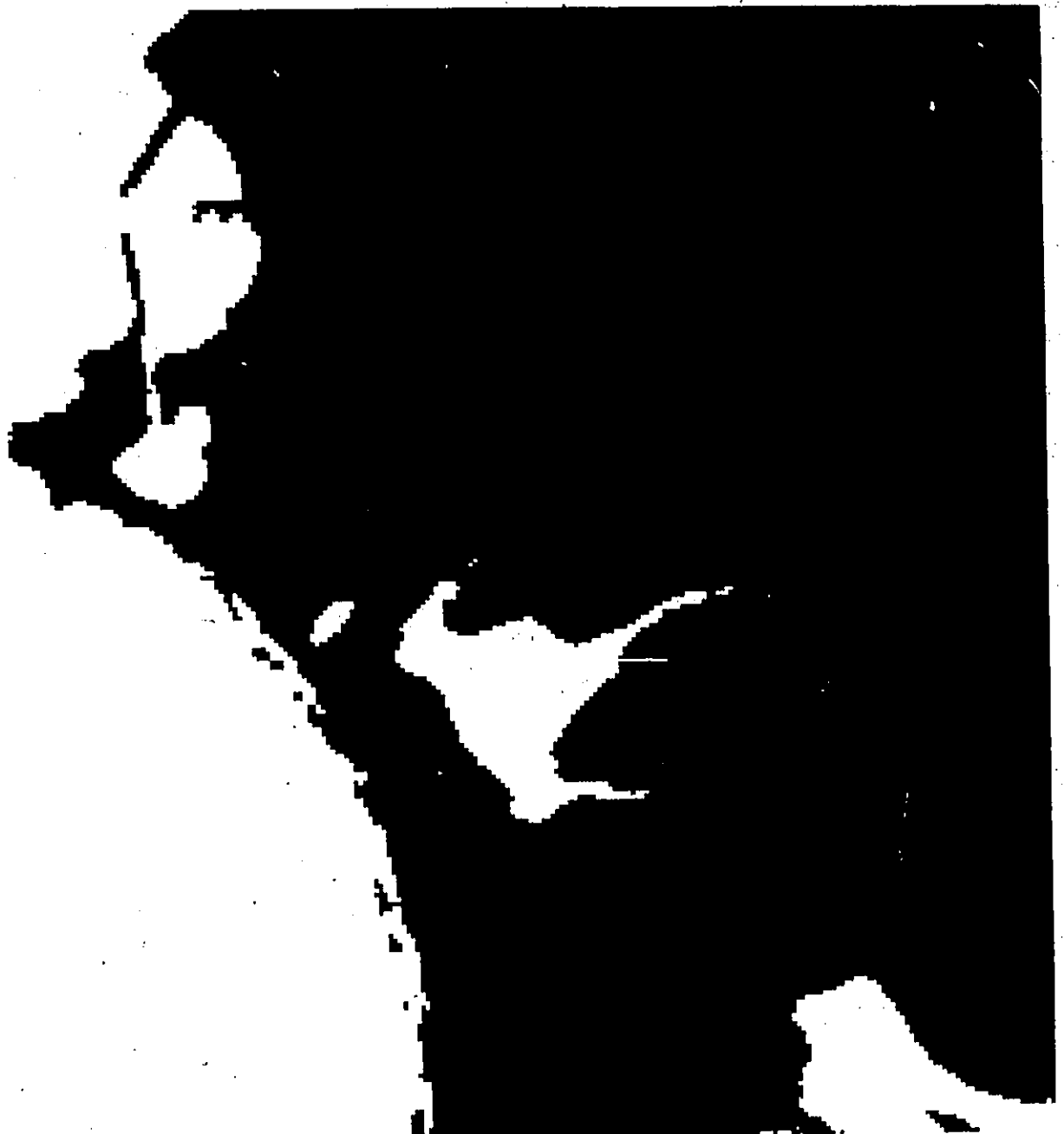


Figure A.2: Madelaine Islands Water/Land Separation: The binary mask was created by thresholding the image in Figure A.1.

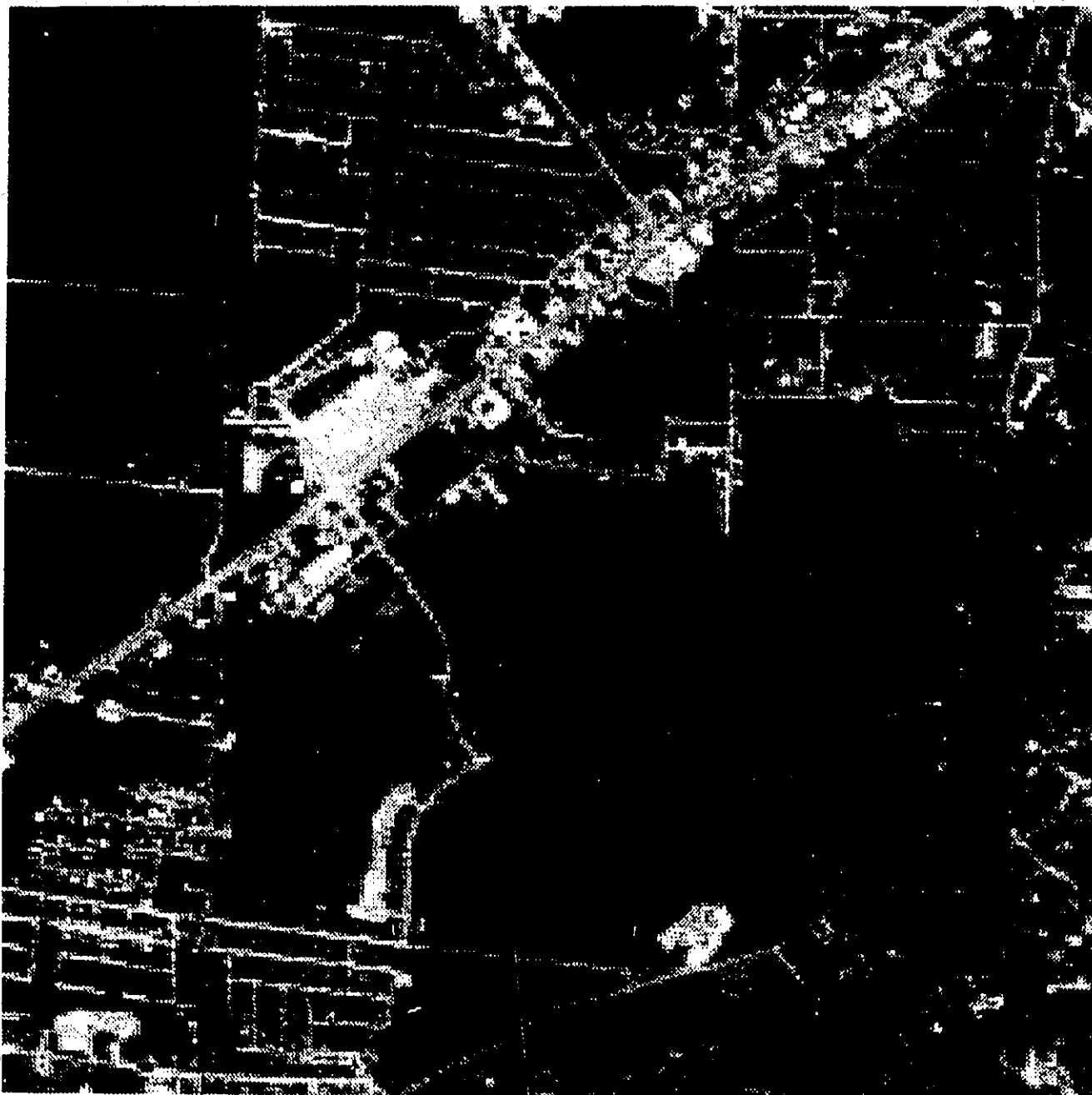


Figure A.3: Sherbrooke (scene 2) SPOT PLA:



Figure A.4: Sherbrooke (scene 2) Extracted Apar Centerlines:

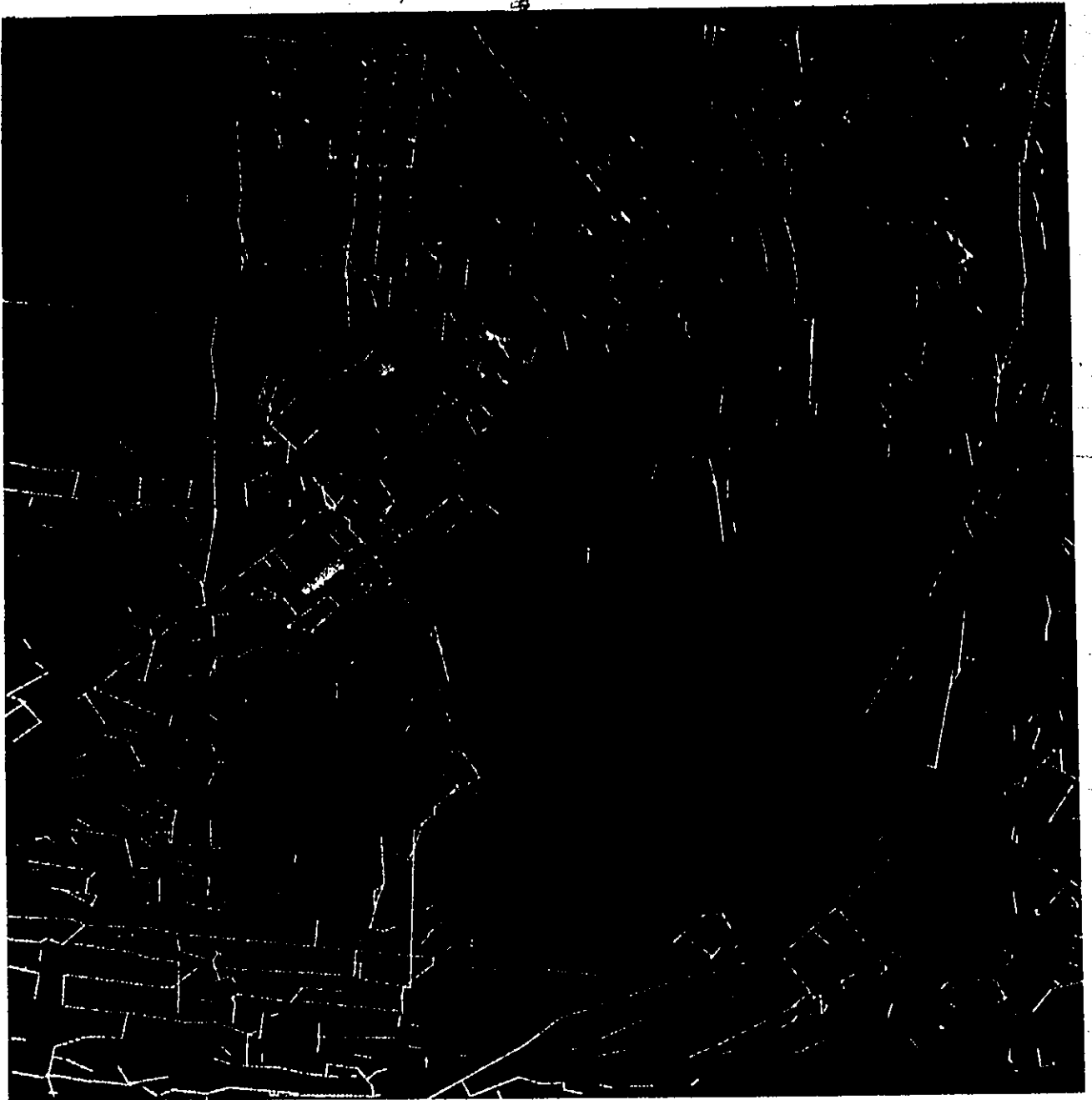


Figure A.5: Sherbrooke (scene 2) Algorithm Results: The overlay graphics are the extracted apars plus the connections which were made by the algorithm.

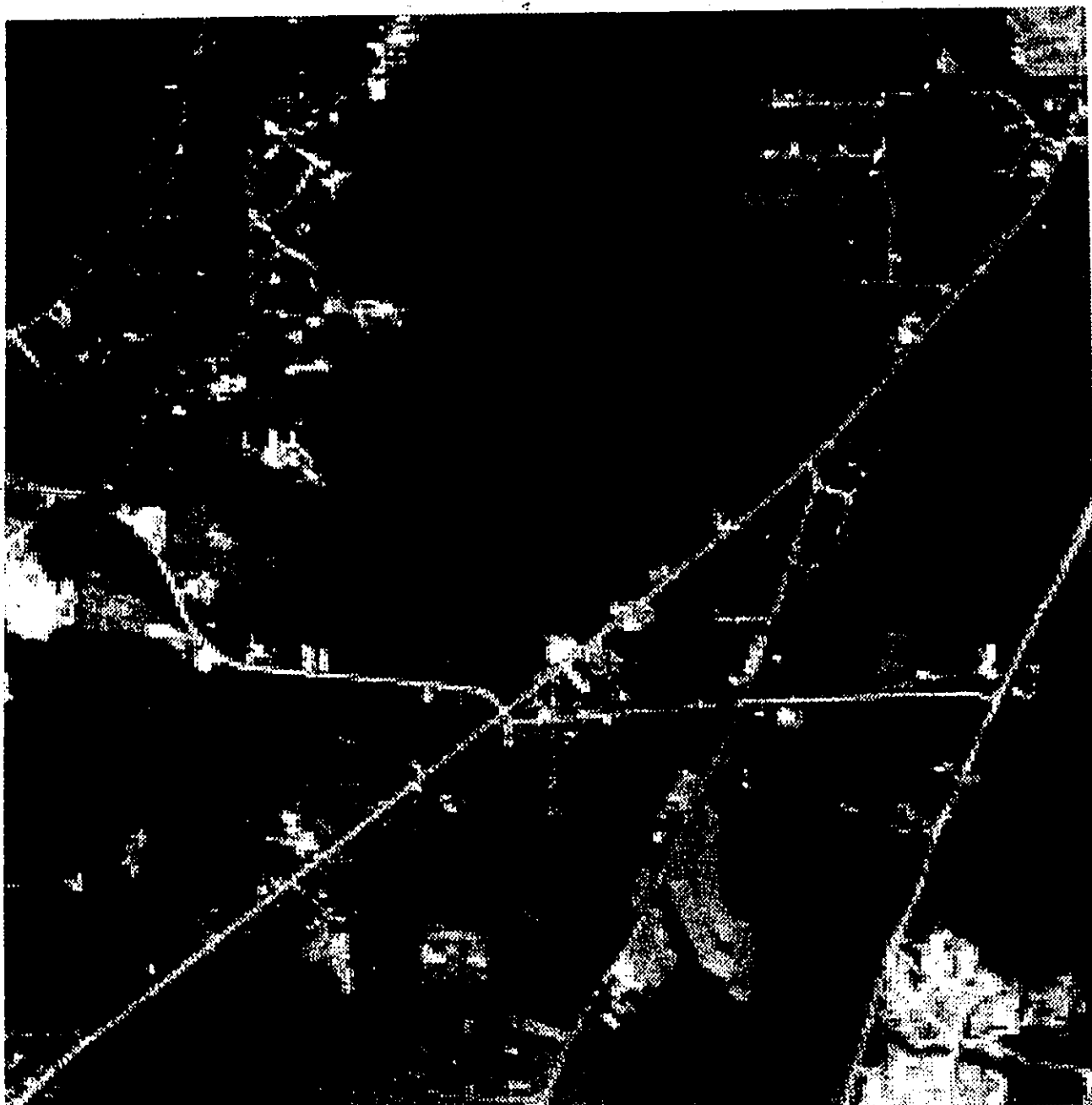


Figure A.6: Sherbrooke (scene 3) SPOT PLA: This image of a farm land area and has similar characteristics to the scene 1 of Sherbrooke.

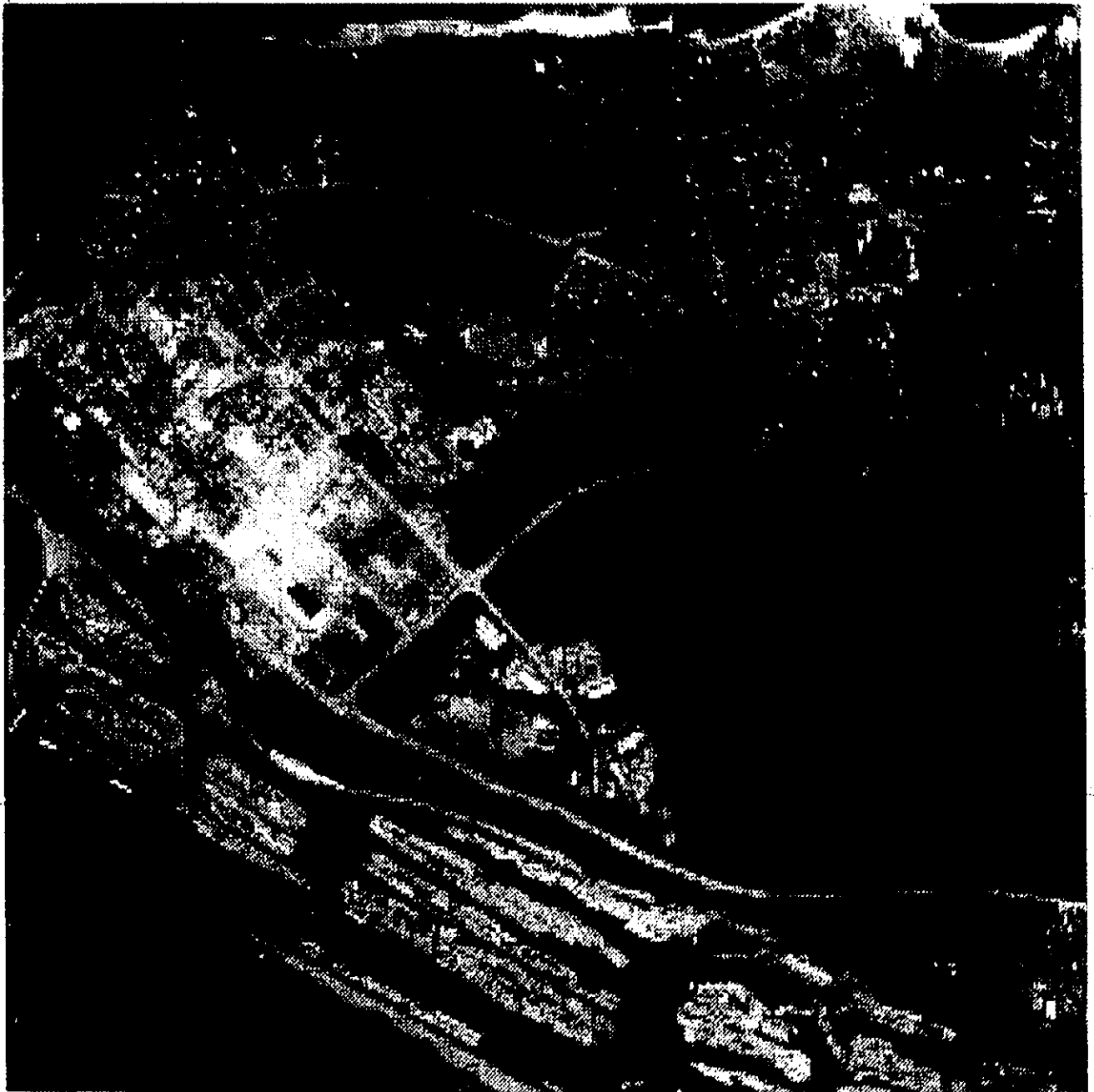
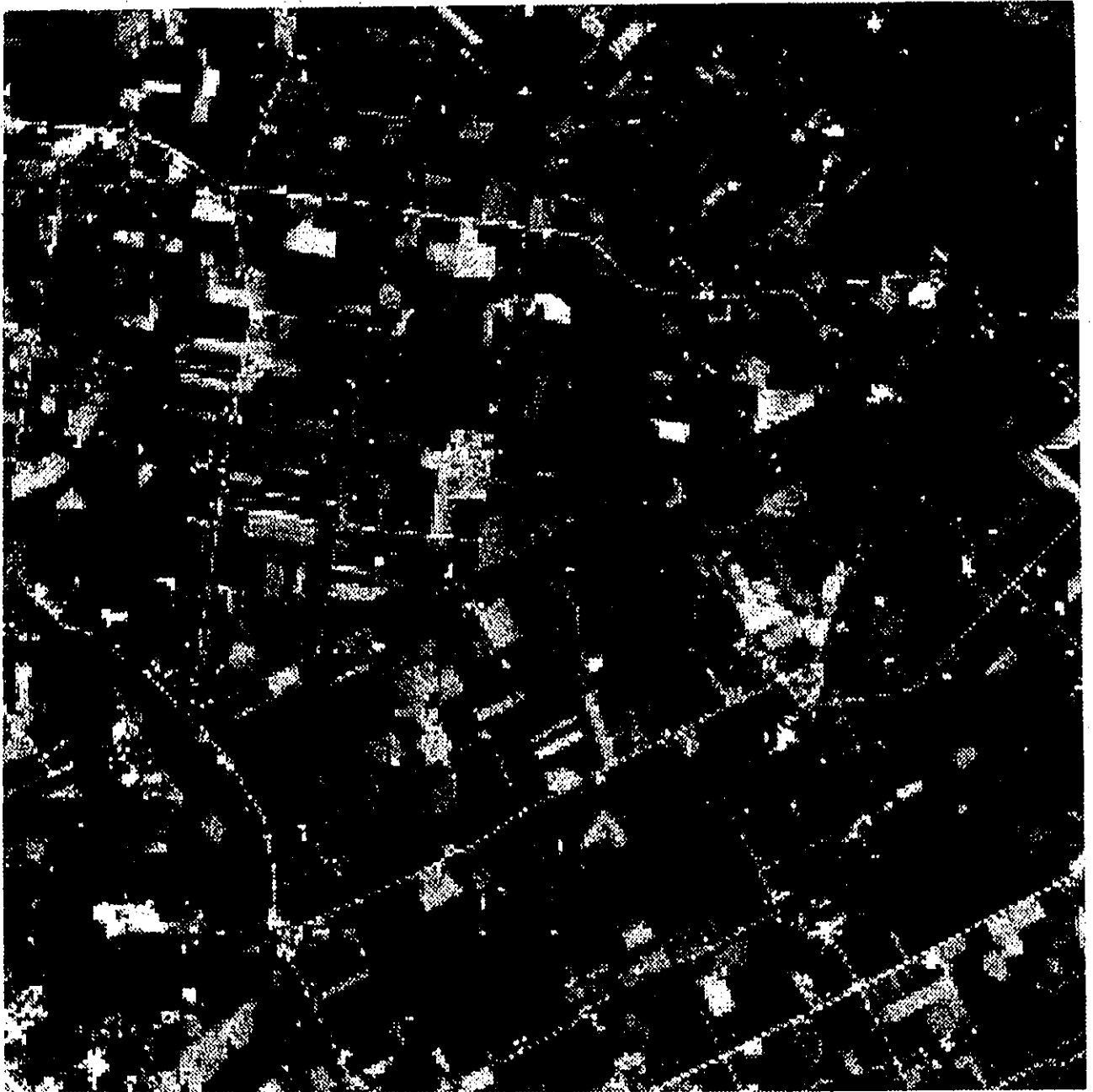


Figure A.7: Vancouver UBC area SPOT PLA: The extraction of apars is difficult in the urban areas as the edges are difficult to make out.



3

Figure A.8: Toronto Landsat TM: This image is of a farm land area near Toronto. The resolution is 30 m. The roads in the image are barely 1 pixel wide. A much smaller filter size is required for the DOG as compared to the one used for SPOT PLA imagery. There are some cases where the road is totally invisible. The connectivity of apar segments might rely more on perceptual clues as opposed to spectral evidence.



Figure A.9: **Vancouver Stanley Park Aerial Photograph:** Digitized aerial photo of a region near Stanley Park. The resolution of the imagery is 1.5 m. At this type of resolution, roads are no longer identifiable as bright narrow parallel strips. There is too much detail in the imagery. Cars, ships, and even road centerlines are visible. In order to identify roads in this scene, context must play a much greater role.