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A Knowledge-Based Approach for Evaluating Forestry-Map Congruency with Remotely Sensed Imagery [and Discussion]

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A knowledge-based approach for evaluating forestry-map congruency with remotely sensed imagery

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[Plate 1]

Simple algorithmic methods for integrating remotely sensed data with existing cartographic databases do not provide satisfactory results. One of the main difficulties is in reconciling spatial differences between the two data sources. The differences are due to such diverse factors as temporal variations, spatial errors in the map data, and topographic effects in the remotely sensed data. To investigate the extent of this data-integration problem, a map–image congruency evaluation (MICE) knowledge-based system was developed which performs three distinct operations: (i) pre-processing for uniform representation of both the image and cartographic datasets; (ii) spatial reasoning on the data with the MICE system; (iii) presentation of a congruency evaluation map. Results are presented for a forested area in British Columbia, where *Landsat* multispectral scanner data are integrated with a provincial forest-cover map.

1. Introduction

Geographic Information Systems (GIS) are computer-based systems for handling map-like information. These can be used to generate maps, to retrieve statistical information and to update the geographic databases, to name but a few functions (Marble 1984). An example of one such system is the GIS used and operated by the Inventory Branch of the British Columbia Ministry of Forests and Lands (BCMOFL), which covers an area of approximately 52×10^{10} m^2 and which must be updated annually with respect to forest depletion (Hegyi & Sallaway 1983). Satellite-based, remotely sensed imagery, because of its large and regular coverage, has the potential for being used for this updating. The process of extracting information from the remotely sensed imagery and its incorporation into the GIS is called 'data integration'. A serious problem that has been noted is the spatial incongruencies between the map and the image data (Goodenough 1988).

Existing databases represent large investments and there can be reluctance to make changes or corrections even when it is recognized that there are errors. Often, the new data elements to be integrated are moved to a location that 'fits' into the map, rather than making extensive modifications to existing elements of the database. This implies that even though the remotely sensed imagery is rectified to the same projection coordinates as the cartographic data, random, nonlinear spatial discrepancies may still exist. This has important implications if automated techniques are to be used for updating the GIS. Somehow, information related to the spatial discrepancies must be acquired.

Algorithmic methods for correlating the map and image data have met with only limited success (Parsons 1984; Billingsley 1982). The essential reason is that features in images do not correlate well with features on maps. However, as maps are produced from imagery (photographs) by experts, a knowledge-based approach may prove to be more productive.

The remainder of the paper is divided as follows. Some background information about photogrammetry, expert systems, and the programming tools used for this research are presented in §2. The map–image congruency problem and a knowledge-based approach are presented in §3. Finally, some examples illustrating the performance of the expert system constructed are provided in §4.

2. Background

2.1. *Photogrammetry*

Photogrammetry is the science of the tranformation of photographs into maps. Most GIS systems today contain map data that were collected, analysed and input by photogrammetric techniques. Older paper maps, that were generated manually, may be digitized and put into a GIS system (Boyle 1980). To understand the nature of errors in a GIS, it is necessary to review some of these photogrammetric techniques.

Photogrammetric data acquisition usually requires taking air photographs with precise altitude, attitude, and positional information. The map is usually then generated by manually tracing desired features from the air-photograph mosaic. The output of the tracing may go directly into a GIS (digitization) or on to hardcopy (scribing).

There are a number of differences between a map and a photograph, which must be taken into account when analysing air photographs. These differences include:

(*a*) maps are drawn to a predetermined scale;
(*b*) maps display only selected features, depending on their purpose;
(*c*) maps emphasize certain selected features;
(*d*) maps display features by using standard symbols;
(*e*) maps are generalized (i.e. some detail is lost);
(*f*) maps are lettered, titled and labelled;
(*g*) maps are produced based on some standard projection.

When tracing an air-photograph mosaic, the photograph interpreter must use considerable judgement in identifying the features of interest. Some of the clues used in feature identification include the following:

(*a*) natural features often have irregular shapes, whereas man-made features have regular outlines;

(*b*) shadows in the photograph give an indication of the height (or depth) of a feature;

(*c*) adjacency relations give a clue to feature identification (e.g. a road crossing a river would be a bridge);

(*d*) stereo viewing allows one to mentally generate a three-dimensional understanding from two two-dimensional images.

Many of these feature identification clues are so obvious that they are often 'second nature'. However, each of these clues could add essential information to the feature identification problem in an expert system.

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2.2. *Expert systems*

'Artificial intelligence (AI) is the study of ideas that enable computers to be intelligent' (Winston 1984, p. 1). AI encompasses a number of domains including natural language understanding, problem solving, robotics and vision, and expert or knowledge-based systems. All expert systems have three common features (Hayes-Roth *et al.* 1983):

(*a*) a human interaction capability to allow human input and machine output;

(*b*) an inference engine to control the deductive reasoning;

(*c*) a knowledge base to store the domain-specific knowledge used by the inference engine.

The architecture and techniques used in expert systems are varied and often complex.

Several rule-based systems for machine perception in remote sensing applications have been developed. Glicksman & Mackworth (1982) researched the use of multiple information sources for image understanding in the MISSEE system. McKeown (1984) and McKeown *et al.* (1985), performed map-assisted photograph interpretation in the MAPS/SPAM system. Plunkett (1986) and Plunkett *et al.* (1986) examined the spatial congruency of forest cover maps and *Landsat* MSS (multispectral scanner) imagery in the MICE system.

2.3. *RESHELL*

One approach to reducing the development cost of an expert system is to use a package called an expert-system shell. A shell contains most of the elements of an expert system except the domain knowledge. The knowledge engineer can easily add rules to the knowledge base of the shell and thus develop an expert system more rapidly. RESHELL (Goldberg *et al.* 1985; Goodenough *et al.* 1987) is an expert-system shell written in Logicware's version of PROLOG, known as MPROLOG.

The architecture of RESHELL is given in figure 1. RESHELL is very modular in the sense that it supports development of a multi-expert system, with individual experts organized hierarchically using blackboards for a communication medium. Each expert in the hierarchy is responsible to a single manager, so that control and communication flow between different levels of the hierarchy rather than across a level. The highest-level expert sets broad goals for the next level of command. The lowest level corresponds to the image-processing algorithms coded in FORTRAN. The two major parts of an expert system are the knowledge base and the inference engine. The knowledge base consists of facts and rules. Facts are the basic information regarding a problem, whereas rules are applied in solving a problem. Rules are in the form of production rules: 'if CONDITION then CONCLUSION'. The inference engine is the scheduler or control mechanism. There are two control strategies that can be followed, namely bottom-up (backward-chaining), and top-down (forward-chaining). Backward-chaining refers to the conclusion being true and finding rules leading to the conditions being true, working backwards from the final goal to the initial state. In forward-chaining, the condition is assumed true and the conclusions are deduced which can be used in other rules leading to the final goal.

Other features presented in RESHELL include a knowledge-acquisition system, a justifier to explain the reasoning of a program, methods for treating uncertainty in knowledge and data, a semantic relation or frames database, as well as an external communications method. The frames database stores data in a manner that preserves descriptive semantic relations between

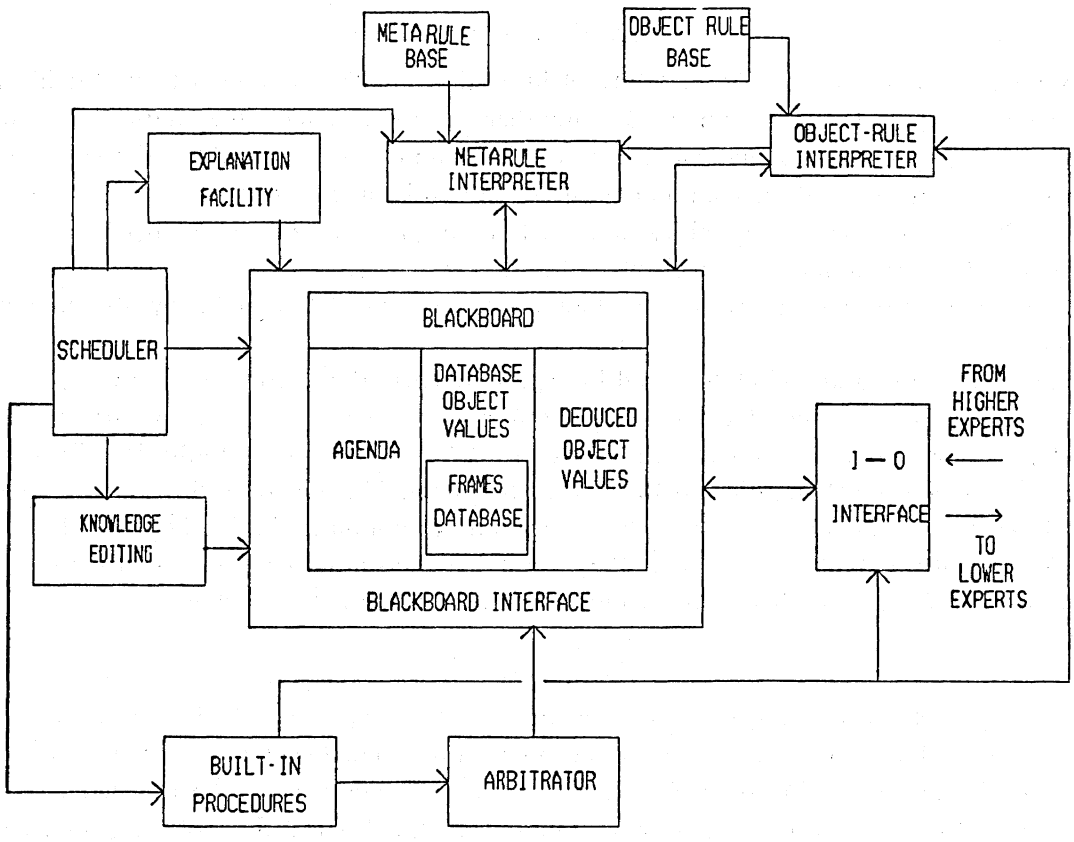

FIGURE 1. The architecture of RESHELL.

objects. The interface to the FORTRAN image-processing algorithms consists of an expert, called the LTI (LDIAS Task Interface), that is responsible for acquiring all the necessary knowledge to execute the FORTRAN code in batch mode, when activated to do so by a higher-level expert. There are two levels of rules: metarules and object rules. Object rules are inference rules that manipulate objects to deduce or prove goals. The object-rule interpreter makes inferences using object rules. Metarules control the metalevel interpreter to select the best appropriate path for the next stage of a solution by manipulating sets of object rules.

The blackboard stores goals from higher-level experts, current object values, the agenda created by the metarule interpreter, as well as the intermediate results. The responsibilities of the scheduler include: receiving messages from the I–O interface; invoking the metarule interpreter; evaluating action procedures in the agenda of the blackboard; and calling built-in procedures when required. The data interface is used for communication among different experts at different levels of the hierarchy. Finally, the arbitrator resolves conflicting results if multiple strategies and/or approaches are used for problem solution.

3. Comparing maps and images

3.1. *The map–image congruency problem*

In the map-making–updating process, photograph-interpreters typically analyse aerial photographs, decide on the classification of the different objects in the photograph, and then transcribe the classification and location of these objects on to a map or directly into a

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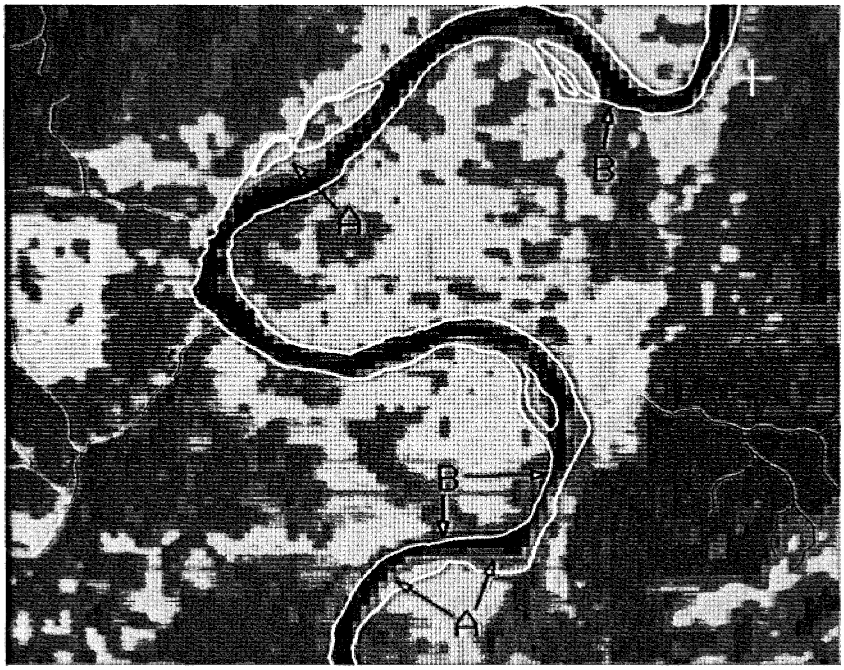

FIGURE 2. River mismatch. Area A indicates land pixels within the map river boundary; area B indicates water pixels outside the map river boundary.

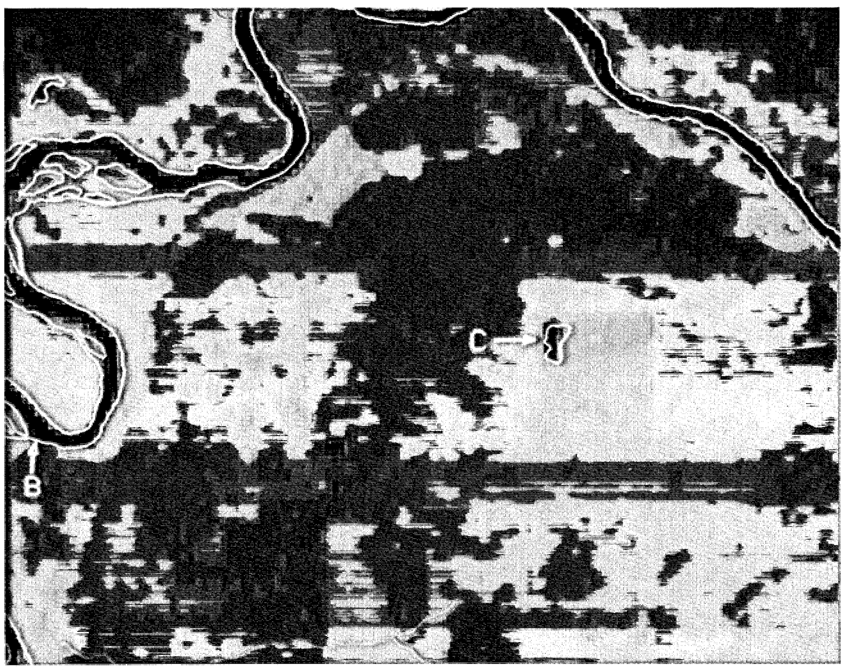

FIGURE 3. Lake mismatch. Area C indicates misalignment of the lake in the map and *Landsat* MSS image.

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geographic information system (GIS) (Zarzychi & Allam 1982). The map is only an approximation to the real world; furthermore, this map-making procedure is prone to human error. A further complication is that the world land-mass is a changing entity. For example, rivers meander, forests burn or are cut, and housing subdivisions and roads are built. Cartographic data, on the other hand, are relatively static and are only updated periodically to reflect the changing world.

The integration problem occurs when some area in a remote-sensing image, which is usually depicted as a polygon, is to be placed in a GIS. If the image polygon is placed directly into the GIS database, then database corruption will occur, if there is not perfect spatial juxtaposition of the image polygon and the neighbouring map polygons. The current method of performing this integration is for a human operator to move the image polygon into the best-fitting location in the map and then place it in the GIS database.

Examples depicting the map–image misregistration problem are given in figures 2 and 3, plate 1. These figures depict a geocoded *Landsat* MSS image overlaid with the hydrography level of the corresponding map. Area A of figure 2 contains pixels that are clearly land in the image, but are categorized as river in the map, whereas in area B the opposite phenomenon has occurred; pixels that correspond to water in the image are categorized as land in the map. Figure 3 is a second example, where the lake in the map appears to be in a slightly different location than the lake in the image (area C).

3.2. *The photograph-interpreter approach*

In dealing with map–image misregistration, an expert photograph-interpreter would be called on to make many judgement calls. Both formal and heuristic rules would be used in making decisions on how to reconcile the two data sources and finally on how to update the map. An expert system paradigm seems to be an appropriate framework for attacking this complex problem. The map–image congruency evaluation (MICE) knowledge-based system (KBS) uses such a paradigm.

Another question that must be answered before selecting a strategy is: how does one know that the map and the image match? A person would look at the map and then at the image, find the corresponding structures, measure their position from some datum, and then report the congruency or discrepancy for the structure. The strategy selected for this rule-based system is not like the human approach. The MICE system performs the same basic operations. These are: (1) pre-process the map and the image to the same spatial datum and symbolic representation; (2) locate corresponding structures (segments); and (3) report on the spatial congruency of the corresponding structures.

There are many types of spatial incongruency. The incongruencies can be random or systematic, local or global, and large or small. The current strategy is simply to report the results and not to try to fix the misregistrations automatically. The evaluation is left to the user.

3.3. *Symbolic representation of maps and images*

One of the first questions that had to be addressed in the design of MICE was how to represent the two disparate data types, map and image data, in a knowledge-based system. This is the iconic-to-symbolic gap problem that is being researched for machine perception systems (Eshera & Fu 1986). Map data containing dots, lines and areas are usually defined in a coordinate reference system in terms of points, vectors and polygons. Image data, on the other hand, are stored by a spatially indexed technique called raster or grid format. It would be extremely unwieldy to attempt to store and process these data in their native form in a knowledge-based system, as the format, data type and resolution of the data are different. Also, the system does not necessarily make decisions based on the data, but rather on various attributes derived from the data. Thus, the uniform method of data representation selected was to pre-process the map and image data into segments and to generate various symbolic segment attributes that can then be used by the rule-based stage.

The next question that needs to be answered is: which attributes of the data are required for congruency evaluation? This question is also not easy to answer, because the image has spectral attributes that are not available in the map data. The image segments' spectral attributes are required, so that the image segments can be spectrally classified. The map and image spatial attributes can be calculated relative to the same reference grid, so that the attribute values of the map and image can be compared and manipulated in a symbolic fashion.

Note that: (1) both the map and the image have been processed to the same spatial resolution and thus can be compared on a pixel basis; (2) this means that the attributes are pixel-size-invariant. Thus the pixels can be any size as long as the map data and image data are pre-processed to the *same* resolution. The spatial attributes selected for use by MICE, that are common to both the map and the image, are as follows:

(*a*) the location of the pixels in the map or image segment, based on some reference grid;

(*b*) the size of the segment;

(*c*) the shape of the segment, here shown as the perimeter squared divided by the area;

(*d*) the smallest rectangle that can be placed around the entire segment (bounding rectangle).

In addition, the following are image spectral attributes calculated from the satellite image that are used in MICE processing:

(*a*) MEAN_CHANNEL_X, the mean grey-level value of channel X for the pixels in the segment;

(*b*) MAX_CHANNEL_X, the corresponding maximum pixel grey-level value of channel X in the segment;

(*c*) MIN_CHANNEL_X, the minimum pixel grey-level value of channel X in the segment.

These spectral values can be used to evaluate the spectral classification of the segment. These spectral attributes are by no means an exhaustive list for classification determination, but they do provide a basis upon which other attributes can be added. Thus, a simple classification rule could be as follows: if MEAN_CHANNEL_4 > MEAN_CHANNEL_2 and MEAN_CHANNEL_4 > MEAN_CHANNEL_1 then CLASS = LAND_COVER.

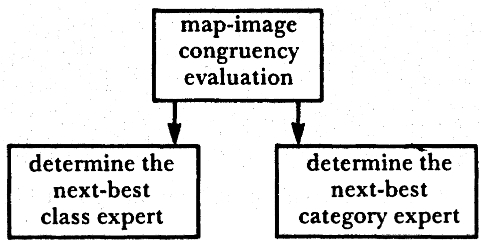
4. Instantiation and illustrative example

Knowledge for the MICE KBS is coded in the form of metarules, object rules and object values. The rules and values are stored in knowledge-base files that are input when an instantiated RESHELL expert is invoked. The MICE KBS uses metarules and object rules that are input from the knowledge base (long-term memory). The object values required for MICE processing are read in from the symbolic map and image files (short-term memory).

The role of the metarules is to establish the general procedure or strategy that is to be applied.

The object-level rules, on the other hand, contain the mundane details of the strategy that is being applied. As an example, there could be a metarule that states that the first action is to read in some file. At the object level, the corresponding rules could concern which portions of the file could be used.

RESHELL supports a hierarchy of intercommunicating expert systems. The advantage of this approach is that the problem can be decomposed into manageable portions, with limited interaction. For the map–image congruency evaluation expert the following decomposition, shown in scheme 1, was chosen. The role of each subexpert is as follows: (1) the map–image



SCHEME 1. Hierarchical organization of the MICE KBS.

congruency evaluation expert is the highest-level expert controlling the input, processing and output of the KBS; (2) the next-best class expert returns the next-best class selected for congruency evaluation; (3) the next-best category expert returns the next-best category of the current class, selected for congruency evaluation.

The knowledge base required by the RESHELL architecture is such that one expert does not have access to the rules in another expert's knowledge base. In other words, the knowledge in the form of rules for each of the three MICE experts is separate and distinct.

Both the best class expert and the best category expert contain metarules and object rules that define the next best category, based on the current class and category. The class and categories were derived from the Canada Council on Surveys and Mapping list of categories of classes.

MICE has been tested by comparing the hydrography levels of a 1:20 000 scale BCMOFL forest cover map with the water features found in a *Landsat* MSS image (240 × 275 pixels). For this test, there were 25 metarules in the MICE expert, 20 object rules in the class expert, and 30 object rules in the category expert. The rules used are complex, with multiple conditions and actions. It takes approximately 3 h on a DEC AI VAX station to complete the knowledge-base phase of this comparison. The results were similar to those that would be obtained by a photograph-interpreter, in that MICE identified the same matches and mismatches between the image and the map. The human comparison of the map and the image was performed in less than an hour. The main rules coded into MICE were obtained through discussions with photograph-interpreters.

In the analysis of the spatial congruency, there were two image segments that matched a map segment for all four attributes; i.e. size, shape, class and overlap. These image segments matched map segments 3 and 9 of figure 4. There were an additional four image segments that matched 3 of the 4 possible attributes. These image segments matched map segments 1, 5, 6 and 11. Figure 4 shows the map segments and figure 5 shows the map segments that were selected by matching at least one attribute with its corresponding map segment.

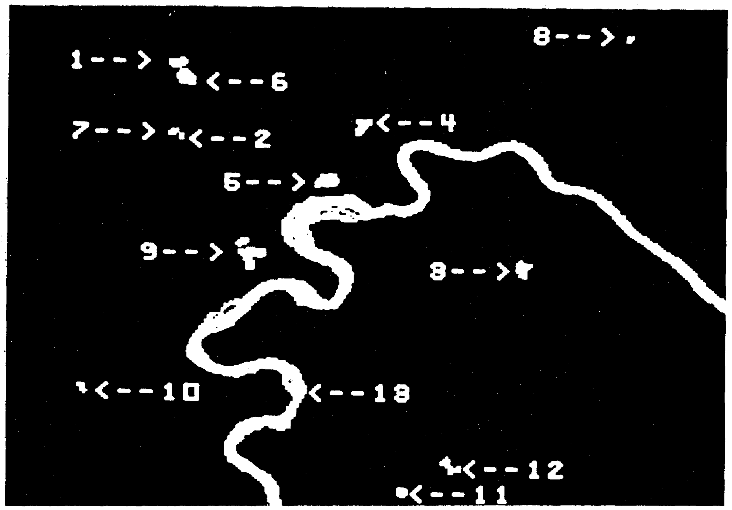


FIGURE 4. The map segments used for locating matching image segments.

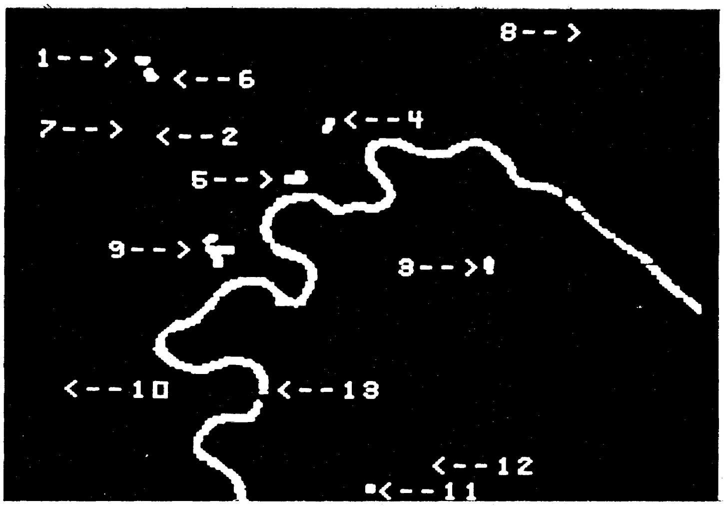


FIGURE 5. Image segments selected by matching a map segment by at least two attributes.

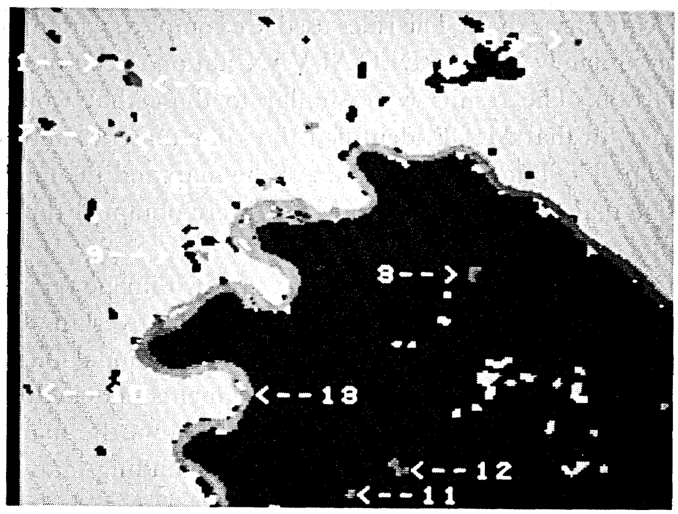


FIGURE 6. Congruency evaluation. The map segments are overlaid on the segmented image, showing areas of misregistration.

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There remain 7 map segments that have no corresponding image segment. These segments are depicted in figure 4. Map segments 2, 7, 8, 10 and 12 were not matched to any image segment as the segmentation operator did not calculate any segments in those areas. Note that these are also quite small map segments. No match was found for map segments 4 and 13 because the segmentation operator generated multiple segments for the river and lake. These problems can be overcome by modifying the segmentation operator and by combining segments, but this is an area requiring further research.

Figure 6 shows the comparison of the congruency of the matching map and image segments. Note that there appear to be no systematic shifts in the map and image data; however, there is not perfect spatial congruency of the matching segments.

Conclusion

The results to date are quite encouraging for the use of a knowledge-based approach for the congruency evaluation of forest cover maps with remotely sensed imagery. In addition, the methods and techniques developed during the course of this research have applications in other processing of map and image data, such as map verification and image classification.

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Discussion

D. Lane (*Intelligent Automation Laboratory, Department of Electrical and Electronic Engineering, Heriot-Watt University, Edinburgh, U.K.*). A well-known problem with blackboard-system architectures is the way in which knowledge sources (KS) may continually retrigger in a cyclic fashion. For instance, the contribution of KS A may trigger KS B, whose contribution triggers KS C. If the contribution of C retriggers A, then a cyclic condition exists. This effect is not always immediately obvious as it may involve large numbers of knowledge sources within one or a number of loops. How does your blackboard-system architecture deal with this?

M. Goldberg. In our blackboard system there is one master (expert) that is responsible for calling up (activating) the other knowledge sources (experts). It is up to this first expert to guarantee that no loops are formed.

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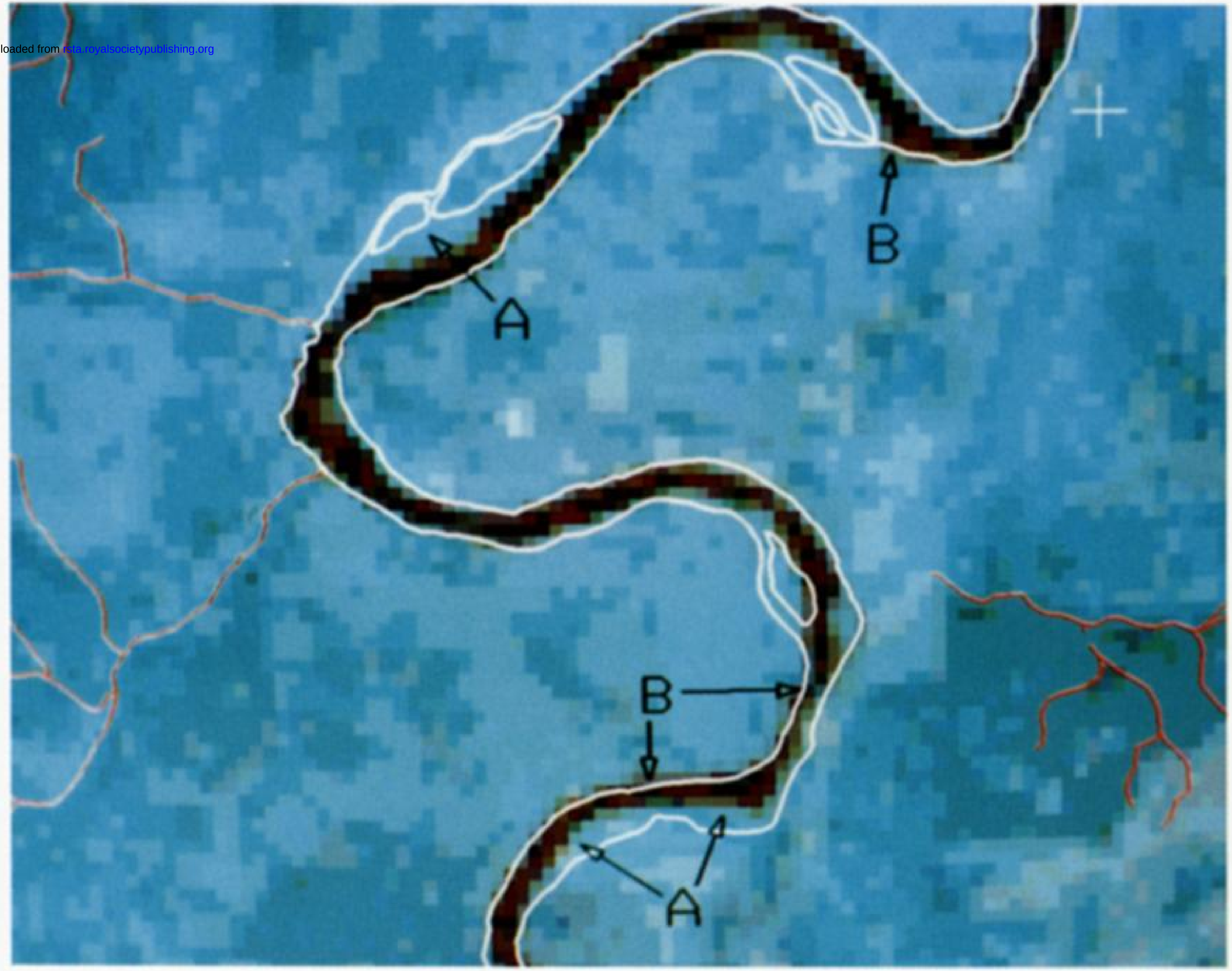

FIGURE 2. River mismatch. Area A indicates land pixels within the map river boundary; area B indicates water pixels outside the map river boundary.

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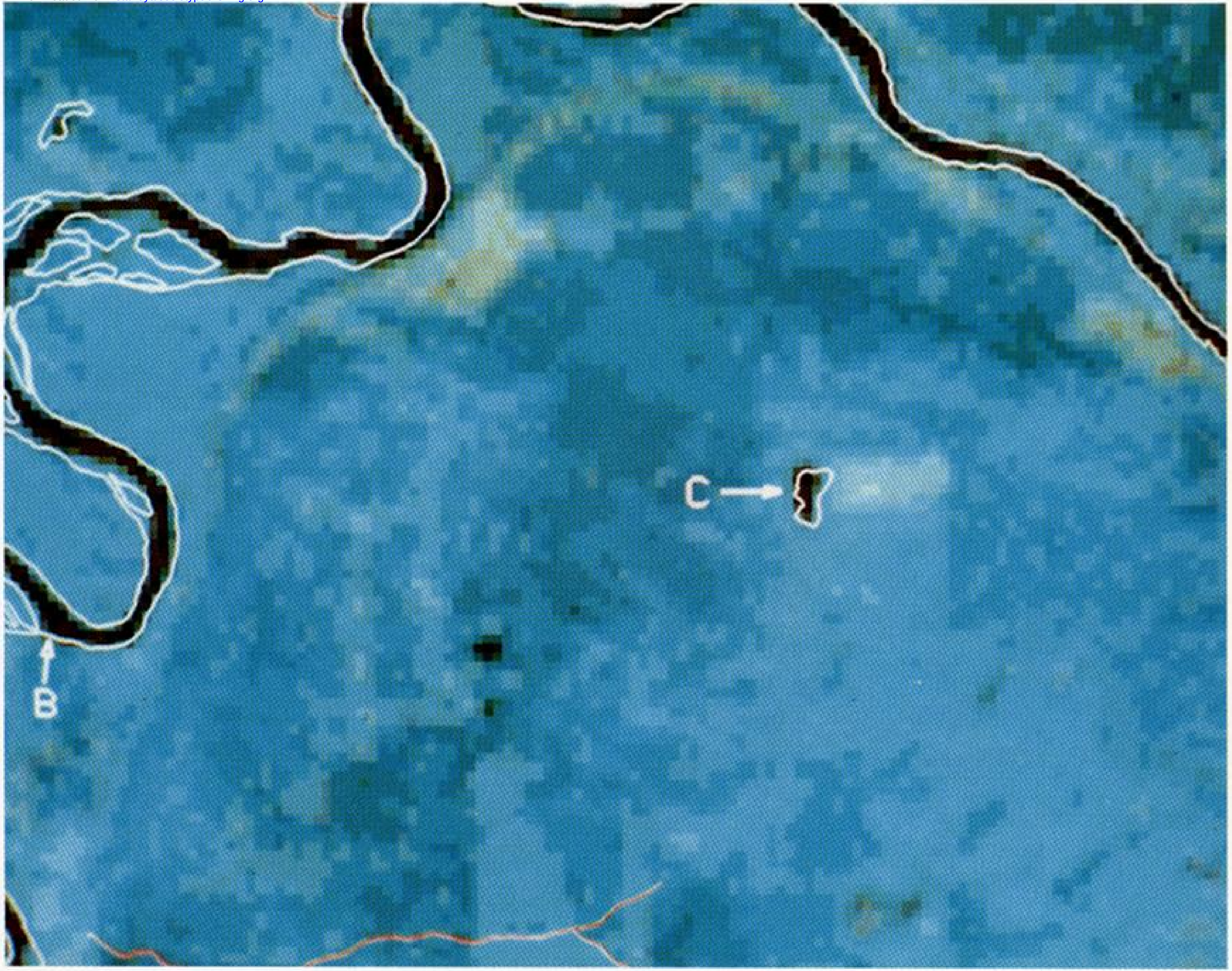


FIGURE 3. Lake mismatch. Area C indicates misalignment of the lake in the map and *Landsat* MSS image.

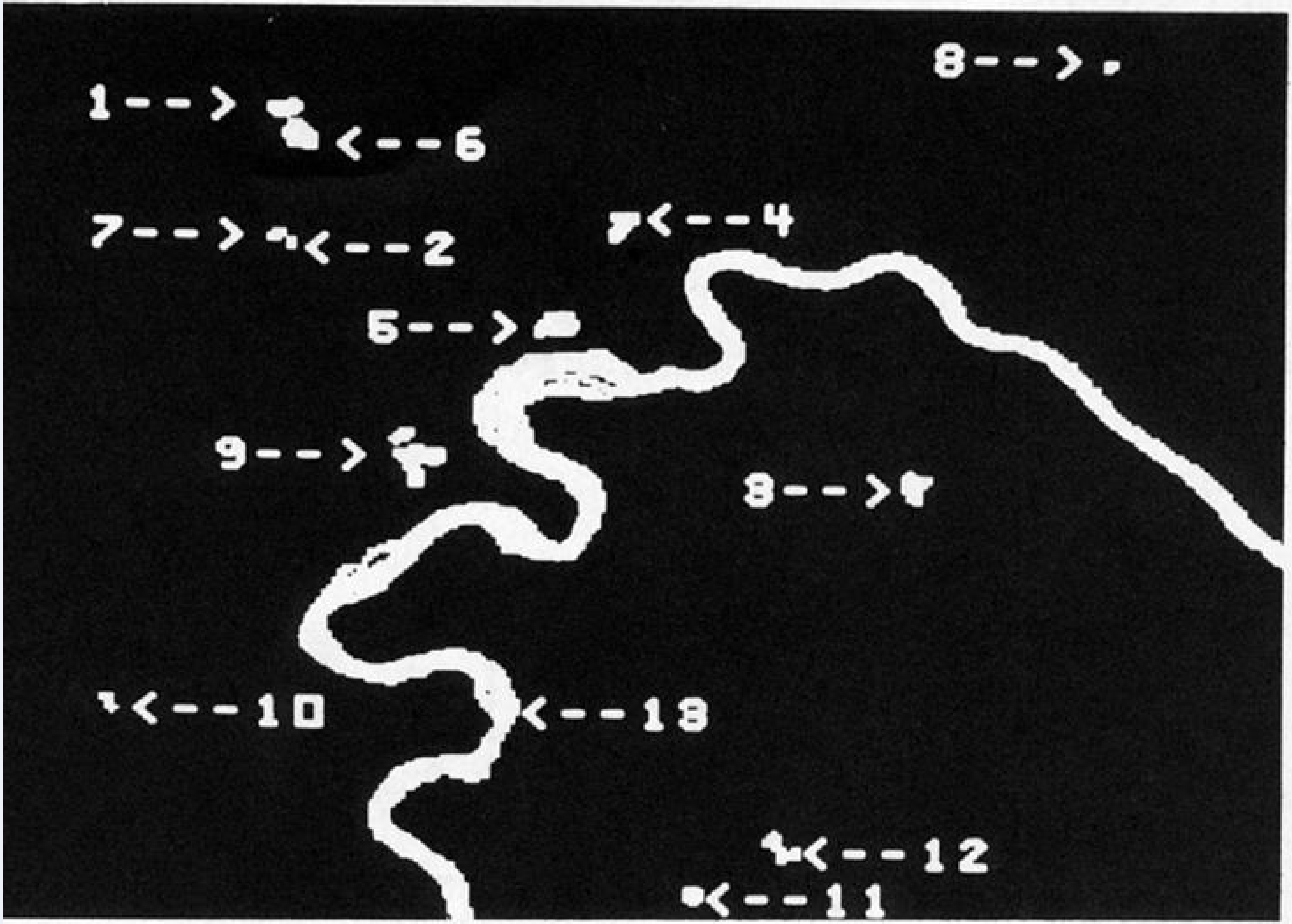
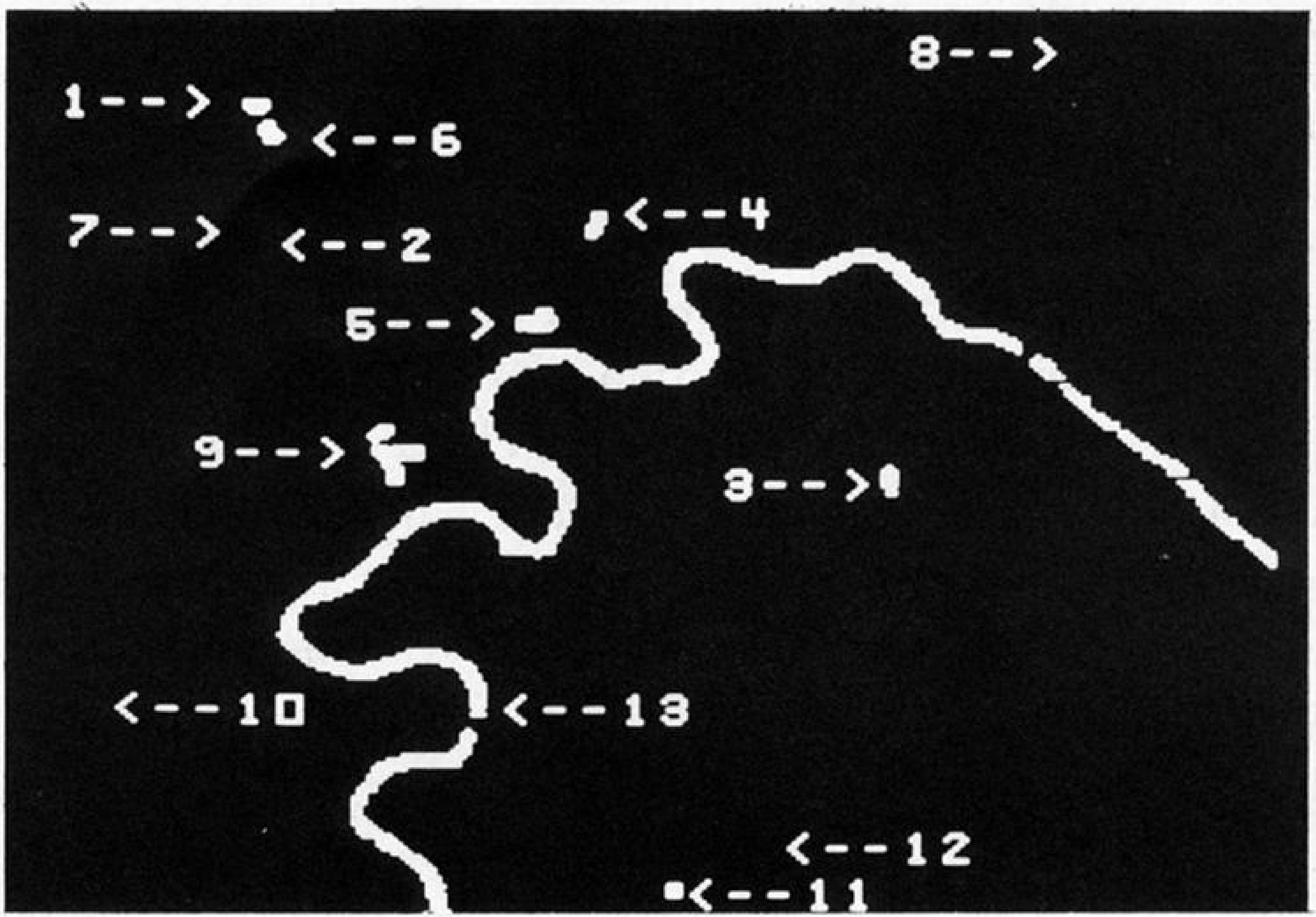
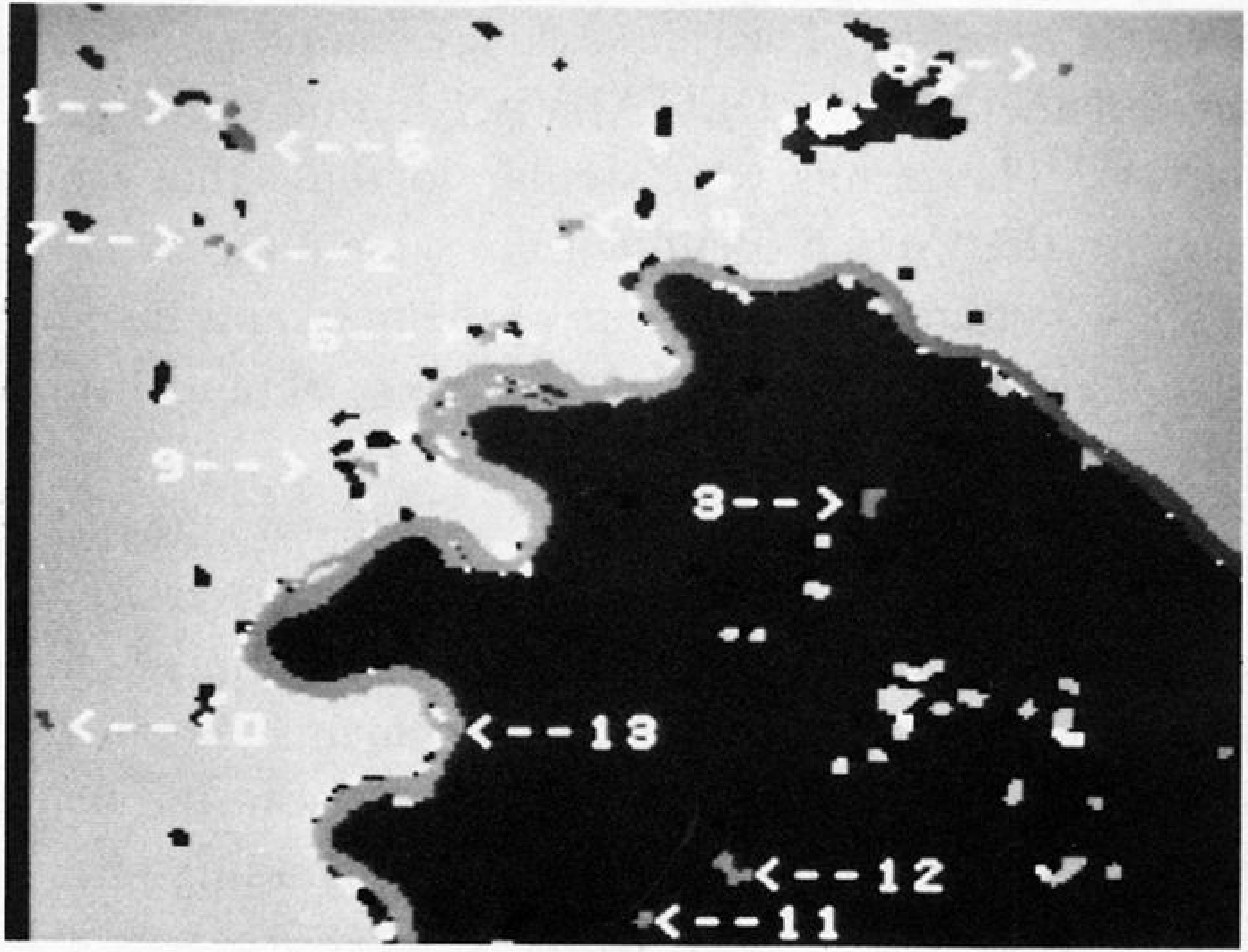


Figure 4. The map segments used for locating matching image segments.



IGURE 5. Image segments selected by matching a map segment by at least two attributes.



IGURE 6. Congruency evaluation. The map segments are overlaid on the segmented image, showing areas of misregistration.

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