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A Machine Learning Approach for Automatic Road Extraction

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Introduction

- **Automatic Road Extraction**

  - concerned with development of computer vision algorithms for pattern recognition and vector delineation of roads from remotely sensed scenes

  - fundamental step in acquisition and maintenance of geographical databases

- **Machine Learning and Parameter Tuning**

  - many extraction algorithms exist, but heuristic or with manually tuned parameters

  - parameter tuning is key to success of fully automated methods

- **Novel Automatic Method**

  - based on fast marching level set method

  - machine learning for parameter tuning

  - information fusion for refinement of object delineation

System Overview

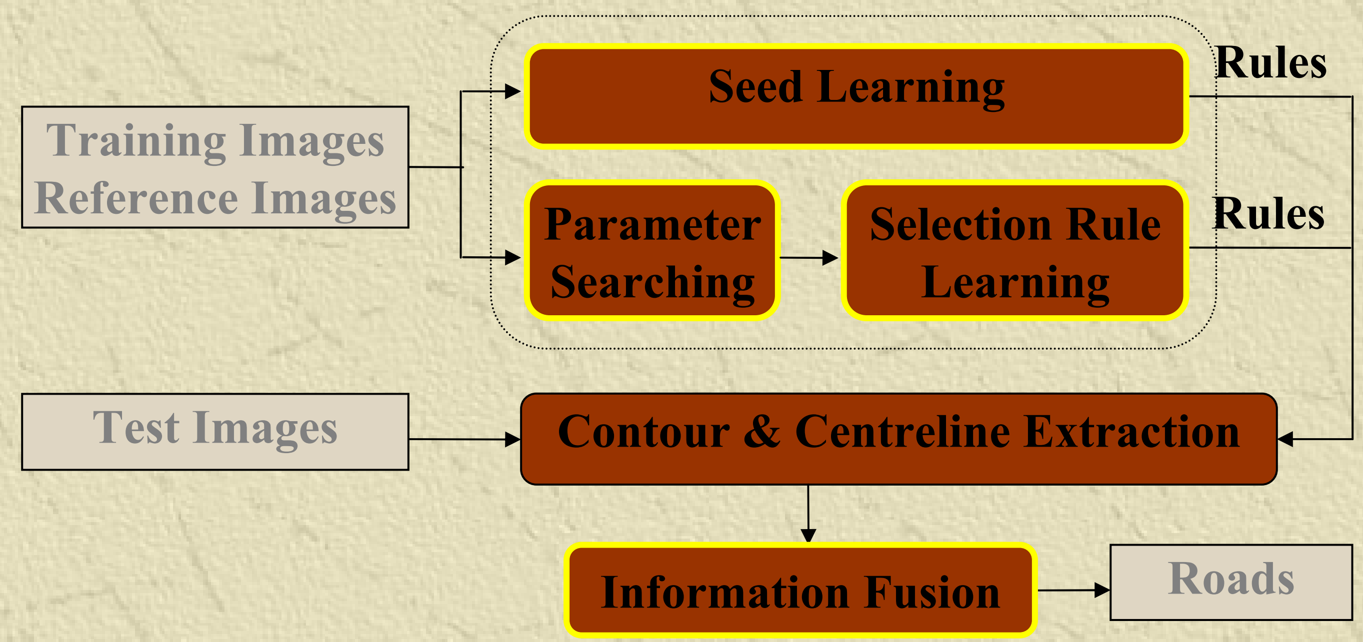


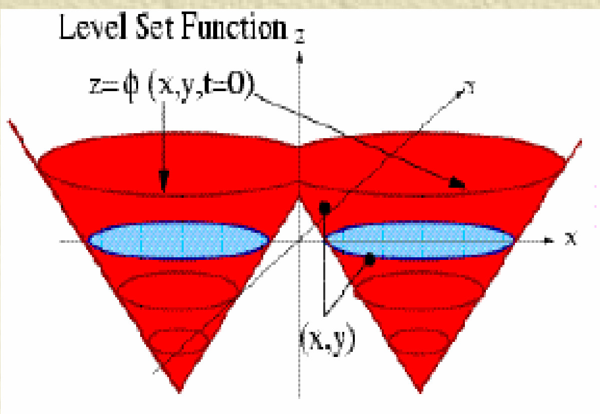
Figure 1 Overview of the proposed system

Fast Marching Level Set Method

- **Similar to, but has advantages over, classic "snakes"**
  - consists of a moving contour, and
  - user defined terms for introducing speed constraints
- **Smartly handles sharp corners and topological changes**

Fast Marching Level Set Method (ctd)

Let γ_0 be a closed, nonintersecting initial curve. Assume $\phi(x,t), x \in R^2$, is a scalar function such that at time t the zero-level set of $\phi(x,t)$ is the curve γ_1, which consists of all pixel x satisfied $\phi(x,t)=0$.



Let $\phi(x,0)=\pm d(x)$, where d (x) is the distance from x to the curve γ_0.

Let such level set of Φ (x, t) = z evolve along its gradient field with speed F. The particle speed ∂x/∂t in the direction n normal to the level set is given by the speed function F.

$$\frac{\partial x}{\partial t}\cdot n = F \Rightarrow \frac{\partial x}{\partial t}\cdot\frac{|\nabla\phi|}{\nabla\phi} = F \Rightarrow \frac{\partial x}{\partial t} = F\cdot\frac{\nabla\phi}{|\nabla\phi|}$$

By the chain rule, $\phi(x,t)=z \;\Rightarrow\; \phi_t + \frac{\partial x}{\partial t}\cdot\nabla\phi = 0 \;\Rightarrow\; \phi_t + F\cdot|\nabla\phi| = 0$

Fast Marching Level Set Method (ctd)

Assume that F > 0, $\Phi(x,y,t) = 0$ becomes single-valued in *t*, i.e. each pixel is visited once. This leads to the fast marching level set method:

$$F\left|\nabla\mu(\mathrm{x},\mathrm{y})\right| = 1, \text{ where}$$

μ - arrival time of the contour
F - the speed function

Combined with an optimal sorting technique, this leads to a very fast solution.

Road Recognition

- Two Problems with fast marching level set method
  - **- Seed selection**
  - **- Parameter tuning for speed function**

- Our Primary Contribution
  - **- Automatic Seed selection (1)**
  - **- Automatic parameter tuning (2)**

- Further Performance Improvement
  - **- Information Fusion at decision level (3)**

(1) Seed Selection

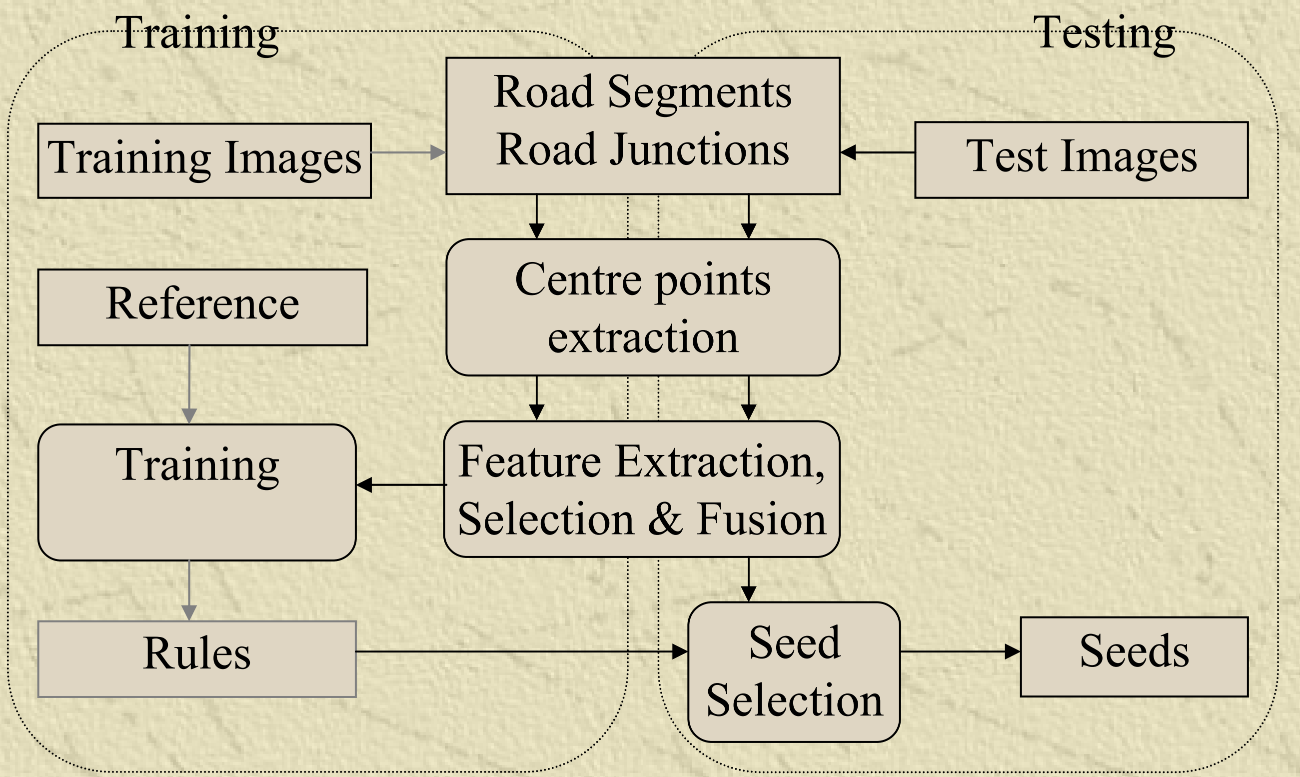


Figure 2 Seeds learning

(1) Seed Selection (ctd)

- Candidate seeds extracted from junction centre points
- Feature subset selection for the seeds
- Feature fusion for combining texture features from candidate seeds and segments
- C4.5 & SVM as learning algorithms
- Stacking for decision fusion
- Texture features (see next slide)

(1) Seed Selection (ctd)

Table 1. Feature List

Co-occurrence Matrix Based	Histogram Based
energy	mean
correlation	variance
contrast	skewness
dissimilarity	kurtosis
homogeneity	energy
entropy	entropy
maximum	
sum	

(2) Parameter Tuning

Speed function formulation due to Keaton and Brokish (2003):

First attempt:

$$\mathrm{F}(\mathrm{x},\mathrm{y}) = \left\{ \left(\mathrm{e}^{-\frac{1}{2}\left(\hat{c}(x,y)-\overline{\mu}_0\right)} + \mathrm{e}^{-\left|T(x,y)-T_0\right|} \right) \times \frac{1}{1+\left|\nabla \mathrm{I}(\mathrm{x},\mathrm{y})\right|} \right\} - 10^{-t}.(1)$$

- $$\overline{\mu}_0 = \frac{1}{n}\sum_{i=1}^{n} I_i, T_0 = \frac{1}{n}\sum_{i=1}^{n} T_i$$
- Add a term 10^{t} to enable learning the speed according to characteristics of the image
- Texture feature vector T is based on the `best' feature subset of a larger feature set

(2) Parameter Tuning (ctd)

Second attempt :

$$F(x,y)=\left(e^{-\frac{1}{2}(\hat{c}(x,y)-\bar{\mu}_0)\Sigma^{-1}(\hat{c}(x,y)-\bar{\mu}_0)^T}+e^{-|T(x,y)-T_0|}\right)\times\frac{1}{1+|\nabla I(x,y)|^P}.(2)$$

- Term Σ and P are parameters that will be automatically tuned

(2) Parameter Tuning (ctd)

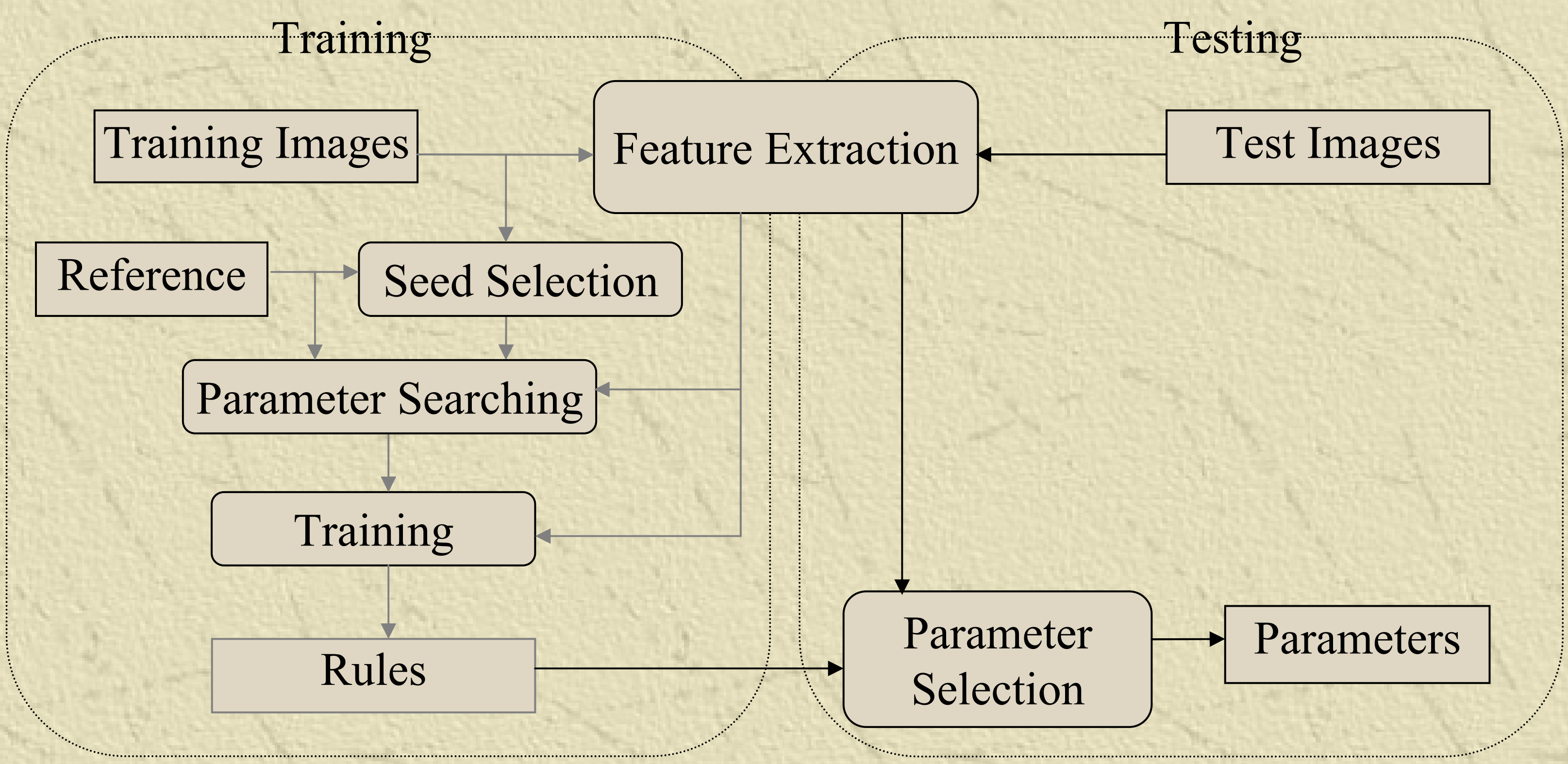


Figure 3 Parameter learning

(2) Parameter Tuning (ctd)

Sequential Search - for Speed Function (1)

- Sequential Search
  Sequentially test a range of parameter values

- Evaluate and Compare
  The extractor itself is used as part of the evaluation function
  Compare the performance for each parameter value attempted

- Select the best parameter value that produces the best performance of the extractor

- SVM regression to learn the relationship between image characteristics and best parameter value

(2) Parameter Tuning (ctd)

Genetic search - for Speed Function (2)

- Genetic Algorithm

    Random search method rather than analytical methods or exhaustive search

    Avoid constructing a complicated model using *a priori* knowledge

    Reduce the computation burden

- Evaluate and Compare – same as sequential search

- Select the best parameter value

- SVM regression for learning

(2) Parameter Tuning (ctd)

```
initialize θ, P_co, P_mut, L n-bit chromosomes
do determine fitness of each chromosome
  rank the chromosomes
  do random select two chromosomes
    if Rand[0, 1) < P_co then
      crossover the pair at a randomly chosen bit
    else
      change each bit with probability P_mut
      remove the parent chromosomes
  until L offspring have been created
until reach the maximum iteration limitation θ
return highest fitness chromosome
```

Figure 4 Genetic Algorithm

(2) Parameter Tuning (ctd)

Training:
  initialize training images and references
  for each training image
    find optimal parameters by GA
    create features
  build parameter selection rules by learning
  return parameter selection rules
Testing:
  initialize parameter selection rules, new images
  for each new image
    calculate features
    find parameters using selection rules
  return parameters

Figure 5 Parameter Tuning Using Genetic Algorithm

(3) Decision Fusion

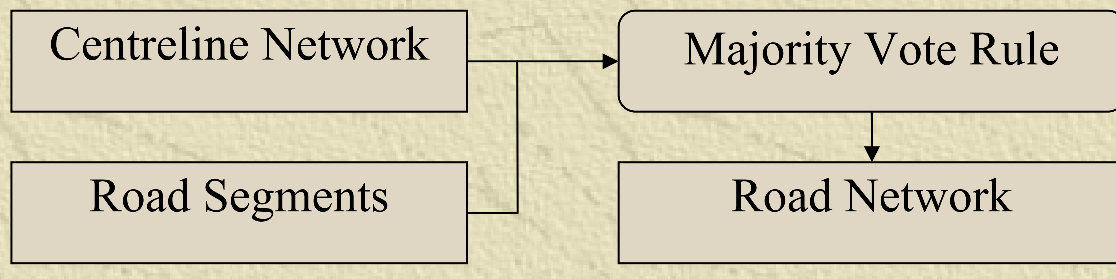


Figure 6 Decision fusion

Majority Vote Rule:

Assign ROAD to $class\ \omega_j$ if $\nabla R_1 \cap \nabla R_2$, *otherwise* NONROAD to $class\ \omega_j$.

∇R_1 *and* ∇R_2 *are the decisions of the individual classifiers.*

Experimental Setup

Dataset

- Dataset consists of 11 grey-scale high resolution remotely sensed images from a rural area.
- Size of each image is 1024*1024 pixels cropped from a larger image of ground resolution 1.3 meters per pixel.
- For experiments using genetic search, each image is further split into 9 patches to construct a 99 image patch training set.
- Leave-one-out cross validation is used in order to learn from the largest available dataset and obtain effective test sets.

Experimental Setup (ctd)

Evaluation Metrics

- We use the centerline vector reference model (Wiedemann et al. 1998).
- Manually delineated references are provided as line vectors.
- Evaluation is performed by comparing the recognized road centerline vectors against manual reference.
- The evaluation measures are given by:

$$completeness = \frac{length_{TP}}{length_{reference}}, correctness = \frac{length_{TP}}{length_{classified}},$$

$$length_{TP} = length_{(reference \cap classified)}.$$

- The two measures above are combined into a general measure of quality:

  CXC = completeness $\times$ correctness^2

  CXC is also used as the fitness for the genetic algorithm.

Experimental Results - Seed selection

- Achieved 89% correctness by leave-one-out cross validation
- Only 4% false positives, causes incorrect object contours and centrelines
- Final centreline was improved by decision fusion

Experimental Results – Sequential Search

Table 2. Results of parameter learning by algorithm one

			Based on learned t			Based on optimal t		
Image	Learned t	Optimal t	Complete	Correct	CXC	Complete	Correct	CXC
1	293	320	42%	100%	42%	42%	100%	42%
2	270	270	61%	93%	52%		-	
3	270	270	49%	82%	33%		-	
4	287	220	18%	100%	18%	9%	100%	9%
5	320	320	52%	100%	52%		-	
6	270	270	23%	85%	17%		-	
7	290	300	2%	78%	1%	2%	78%	1%
8	290	290	49%	68%	23%		-	
9	236	220	85%	92%	71%	81%	91%	68%
10	279	270	11%	75%	6%	11%	75%	6%
11	303	320	13%	100%	13%	16%	100%	16%

Same parameter value

Close parameter value, Same results

Close parameter value, Close results

Experimental Results - Sequential Search (ctd)

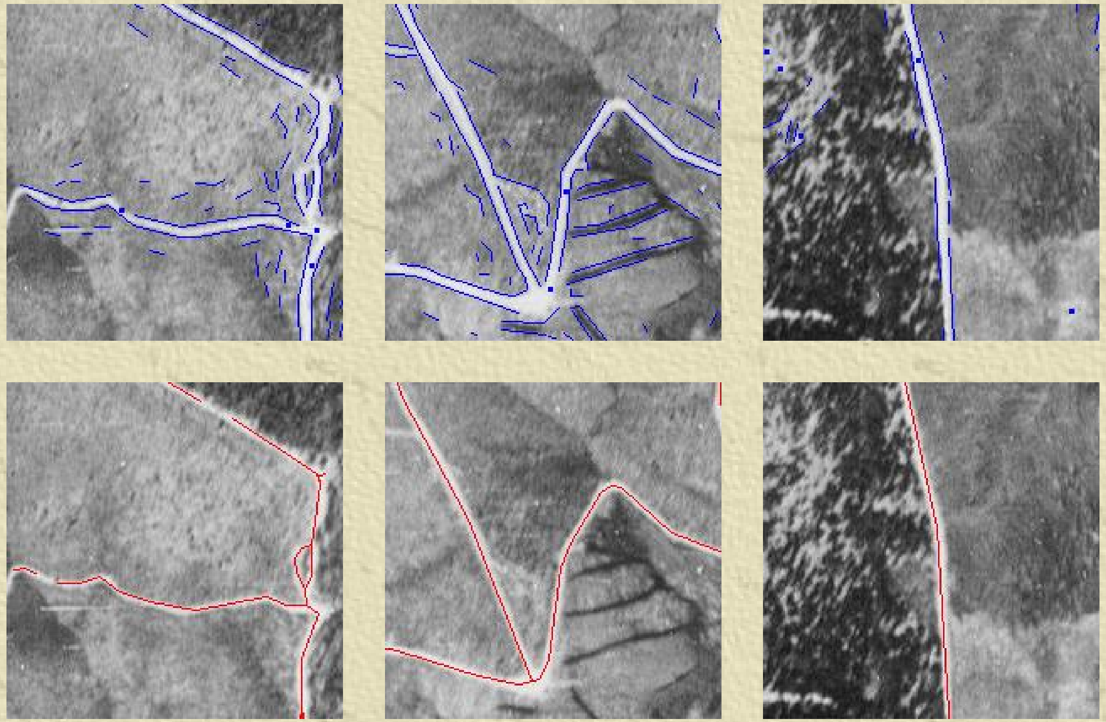


Figure 7 Some experimental results using our method on remotely sensed images by algorithm one

Experimental Results – Genetic search

Table 3. Comparative results for shown images (CXC values) — High CXC is better.

	All (average)	Image A (average)	Patch a	Patch b	Patch c
Learning approach	34%	64%	90%	98%	87%
Standard approach	20%	55%	67%	31%	53%
Improvement	14%	9%	23%	67%	34%

Experimental Results - **Genetic search** (ctd)

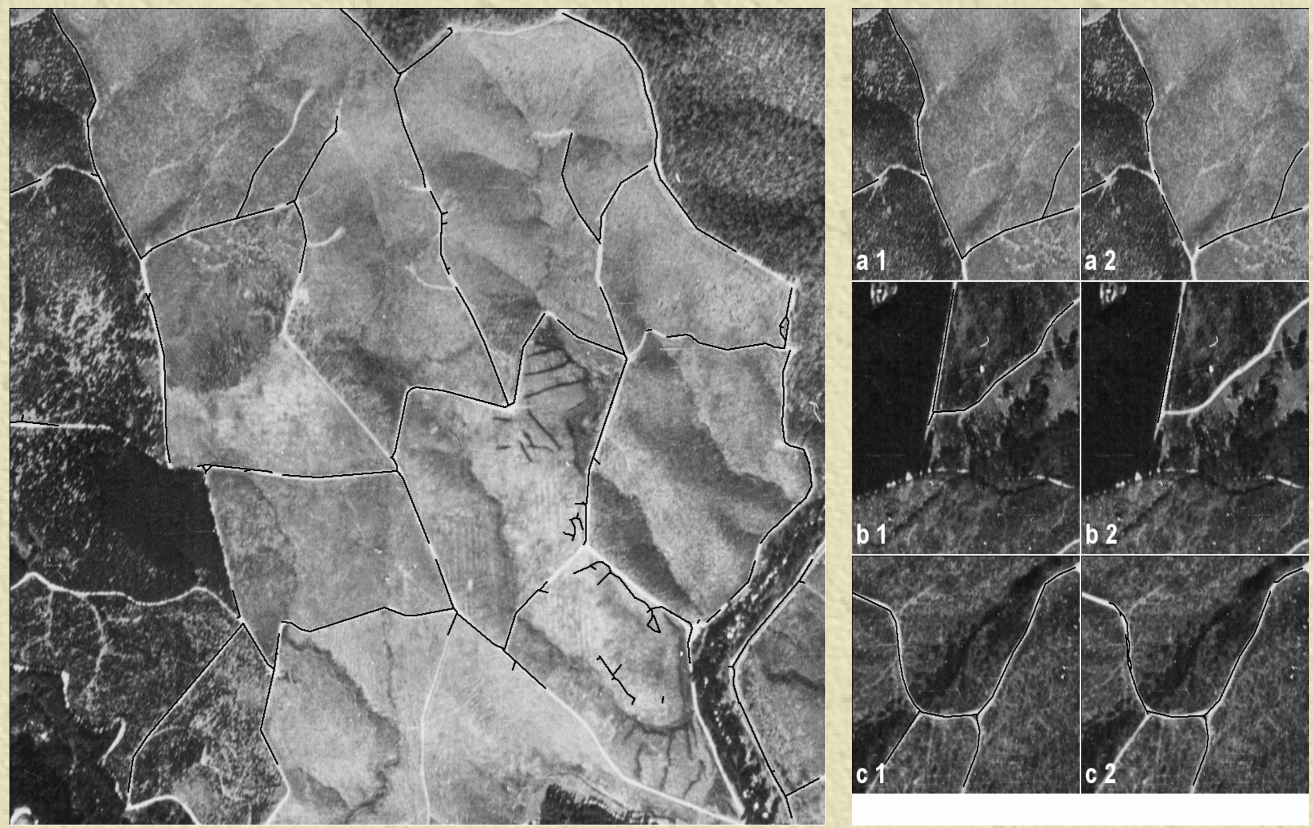
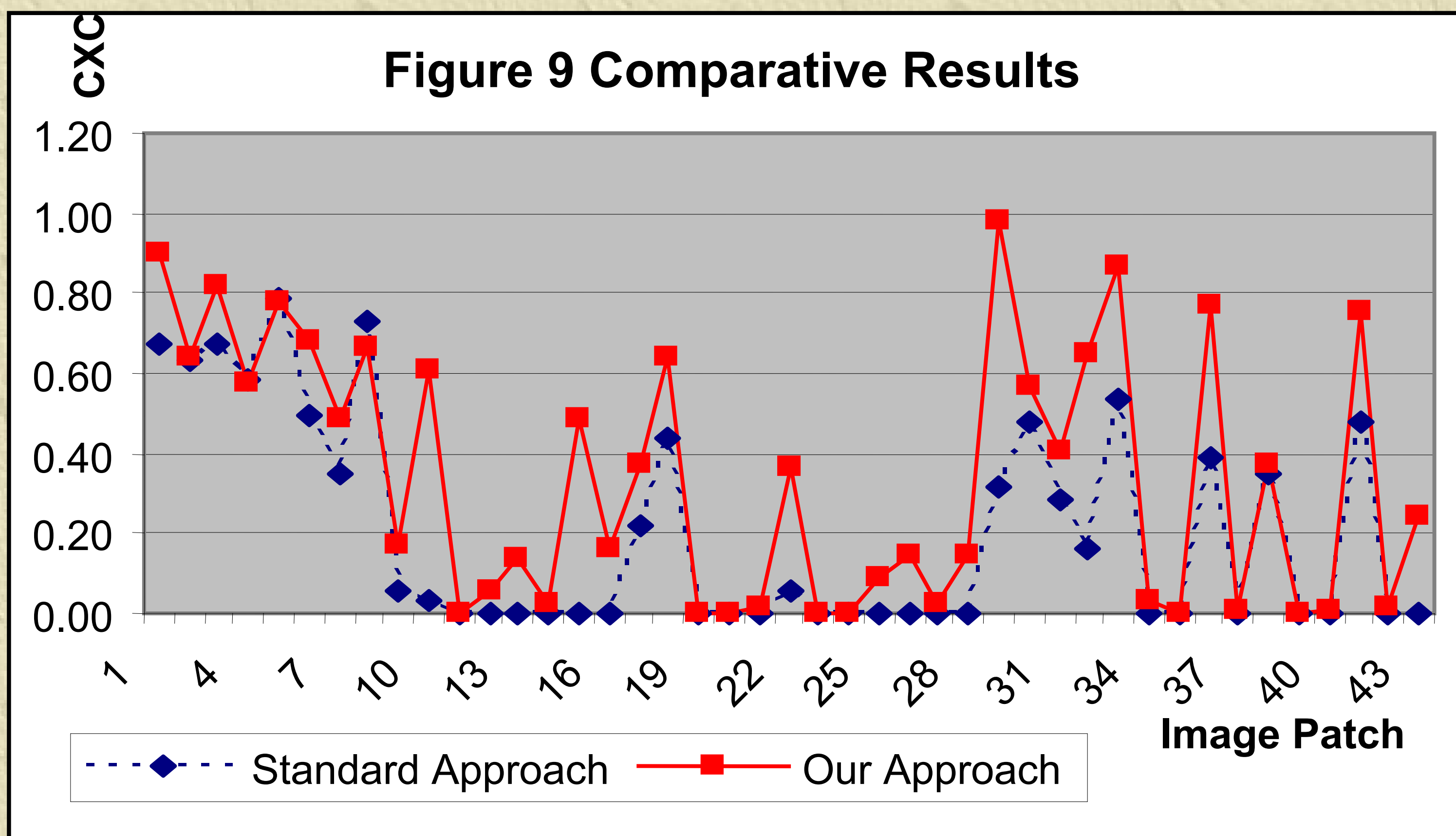


Figure 8

Left: Image A (1024*1024 pixels) by learning approach (CXC 0.64 average).

Right: Patches results: a1, b1 and c1 by learning approach; a2, b2 and c2 by standard approach.

Experimental Results - Genetic search (ctd)



Experiment Results (ctd)

Original Image

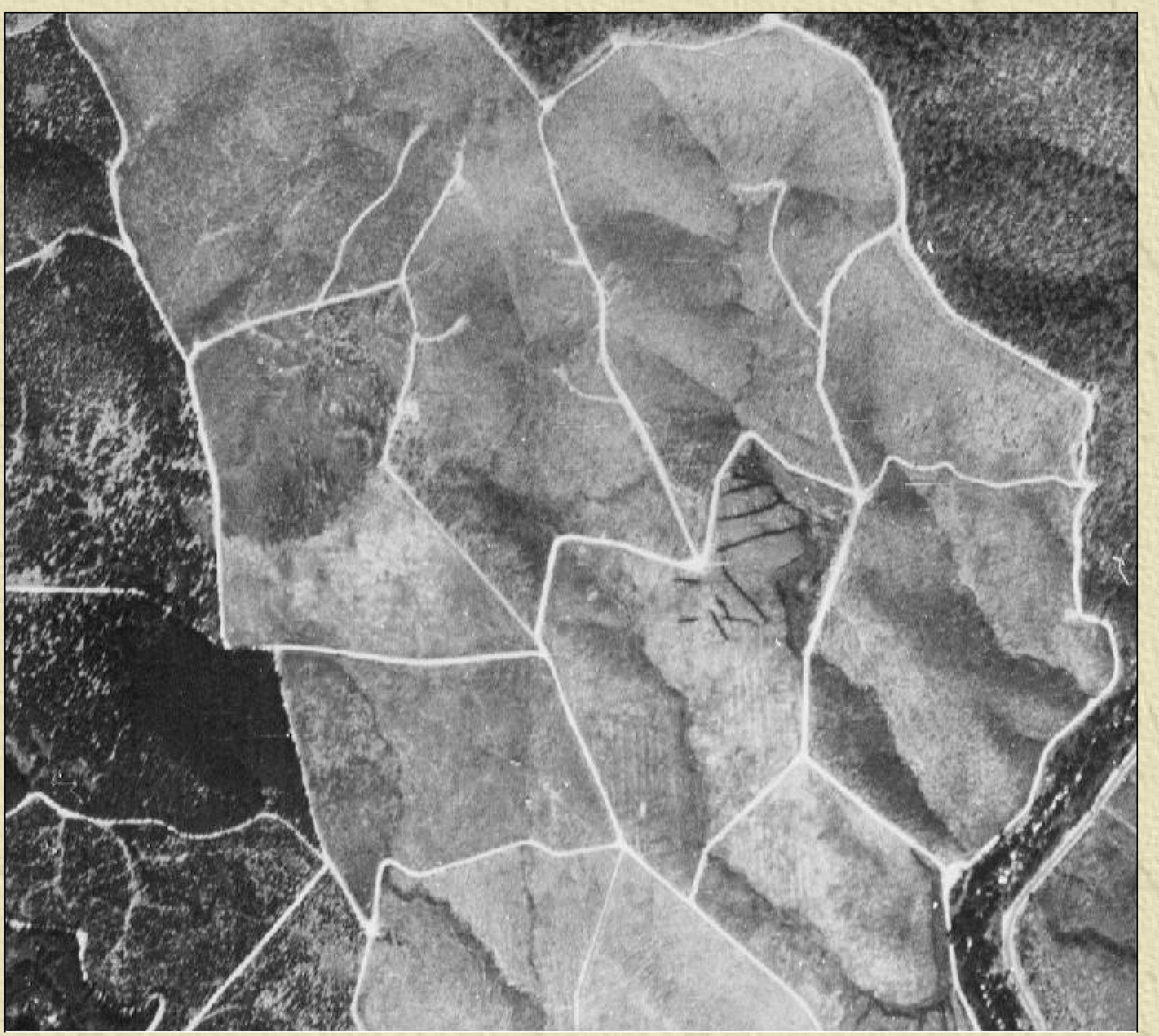


Figure 10-1 Experimental Results of One image Over 4 Steps in the Learning Approach

Experiment Results (ctd)

Edges & Seeds

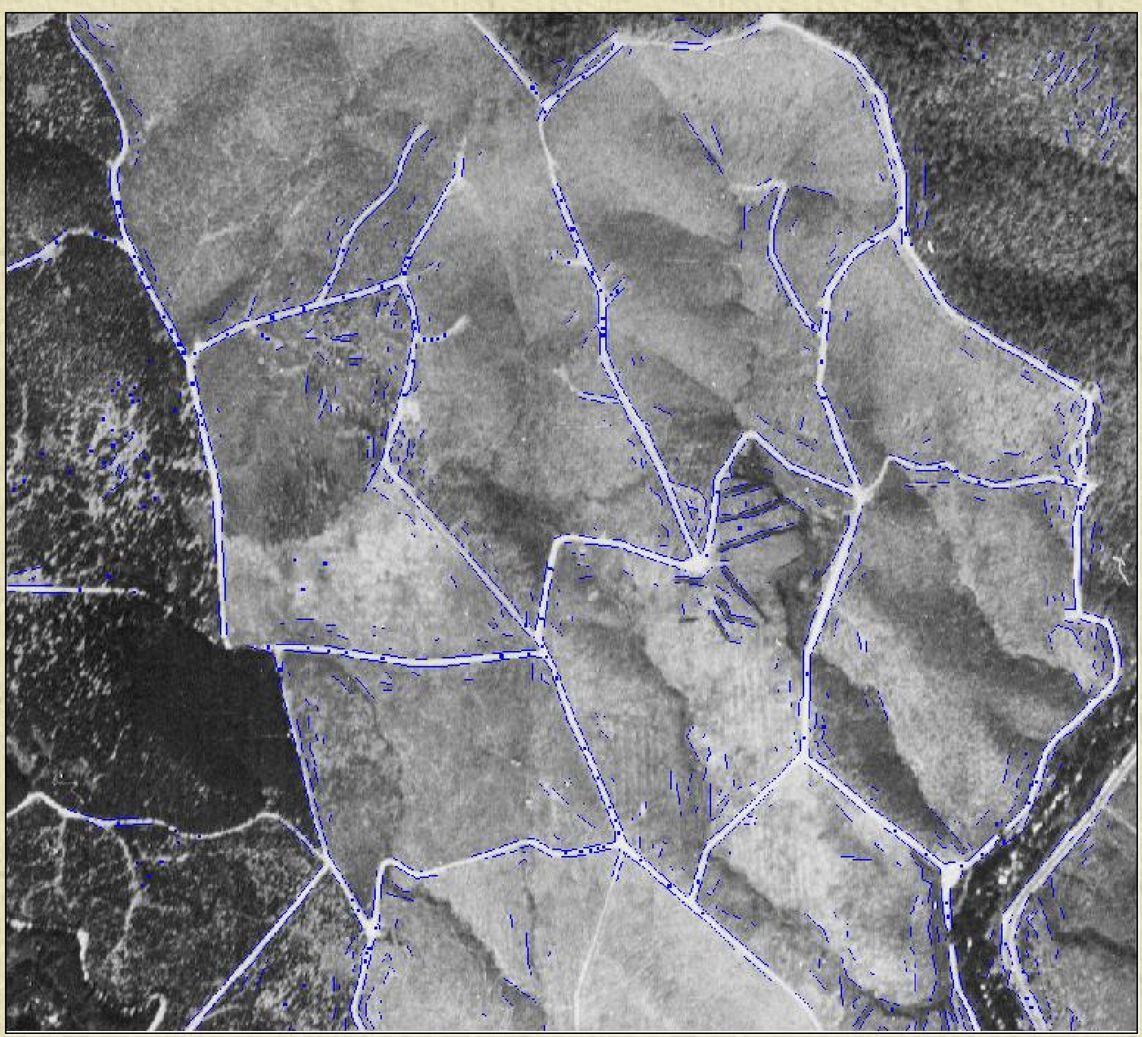


Figure 10-2 Experimental Results of One image Over 4 Steps in the Learning Approach

Experiment Results (ctd)

Contours

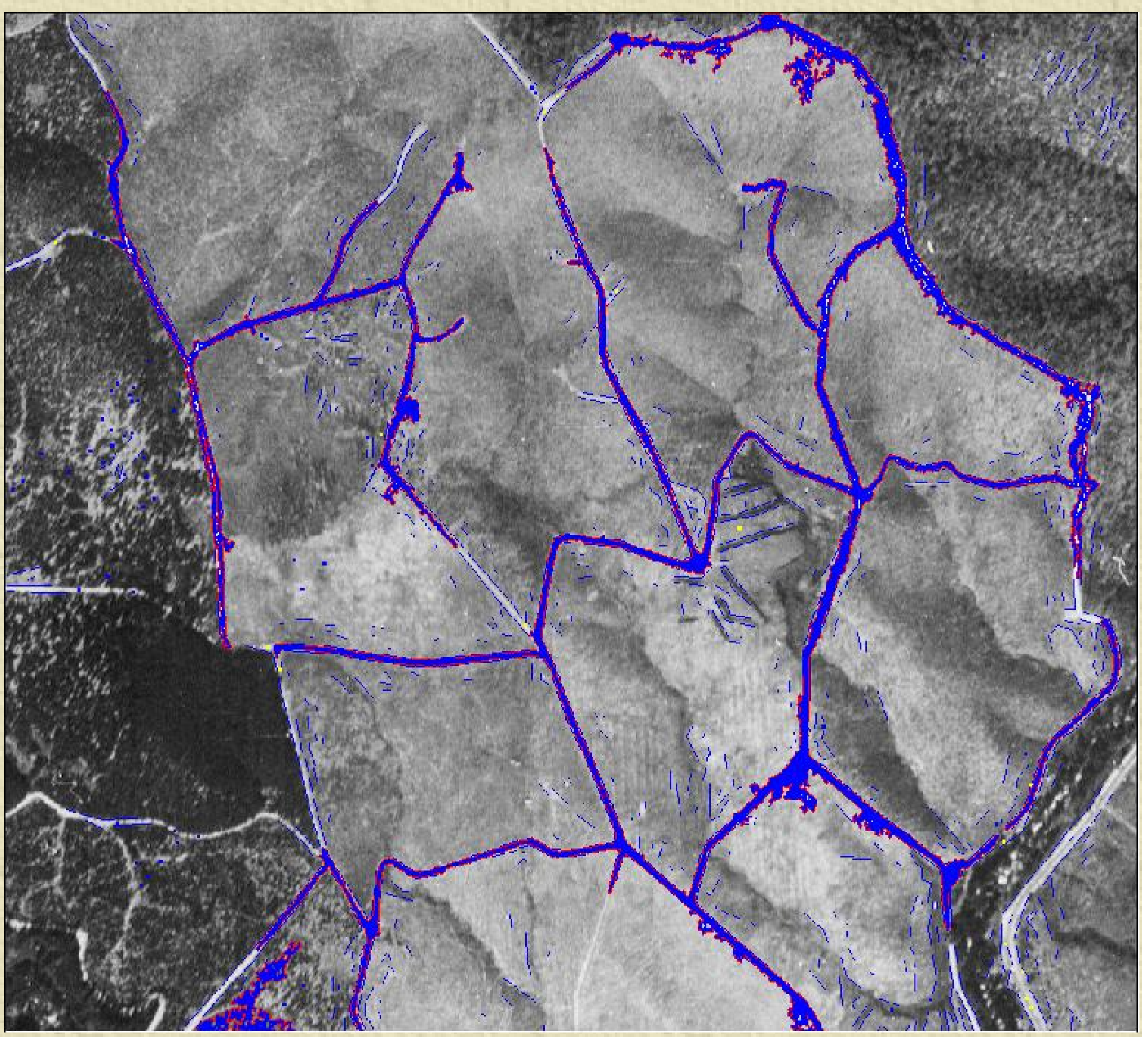


Figure 10-3 Experimental Results of One image Over 4 Steps in the Learning Approach

Experiment Results (ctd)

Centrelines

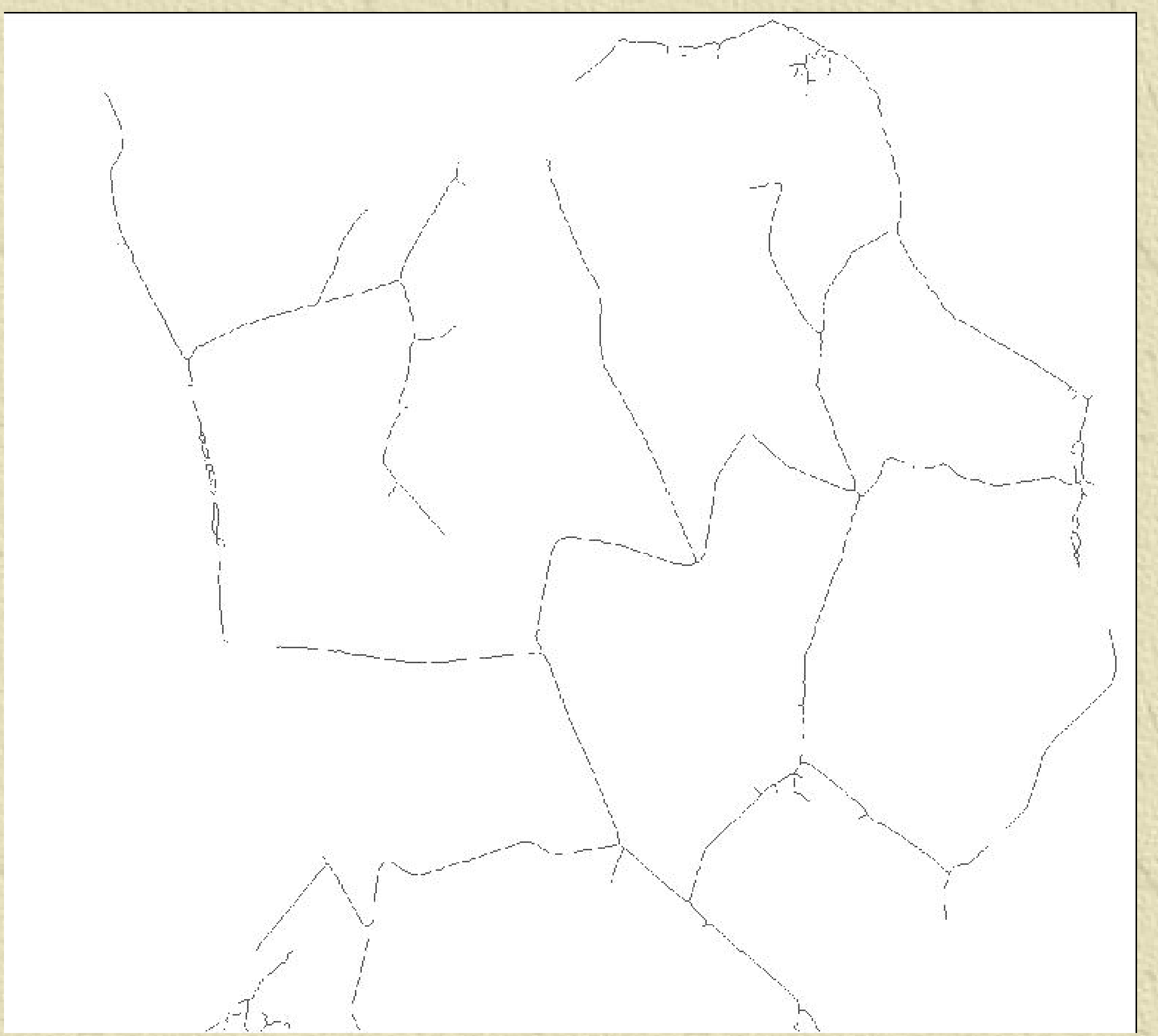


Figure 10-4 Experimental Results of One image Over 4 Steps in the Learning Approach

Experiment Results (ctd)

Mapping Back

Figure 10-5 Experimental Results of One image Over 4 Steps in the Learning Approach

Conclusion

- Region growing approach based on fast marching level set method for road recognition
- Automatic seed selection and parameter tuning using machine learning

  - relationships: seeds class, seed characteristics and image characteristics

  - relationships: parameters and image characteristics
- Information fusion to refine road centreline