A Probabilistic Framework for Automatic Terrestrial Feature Extraction from Remote-Sensed Imagery

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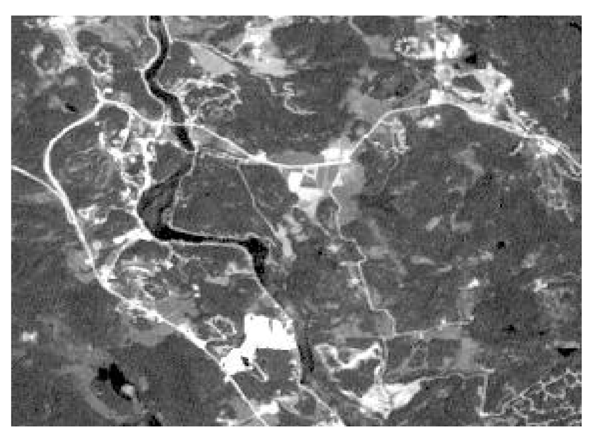
Abstract

This research addresses the general problem of inferring the presence of terrestrial features from multiple sources of imagery. The ultimate goal is to develop fully automatic systems for extracting terrestrial features, based on characteristics inferred from training sets across multiple sources. Our approach uses Principal Component Analysis for the classification of features from training images, and a certainty measure is associated with each recognized feature for subsequent use in accumulating evidence across different information sources (e.g. spectral bands).

Problem

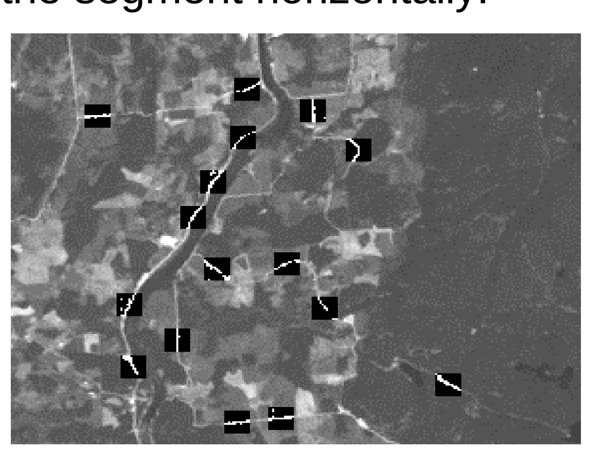
The framework was used on Landsat-7 multispectral data for the classification of roads. However, the framework is general and could easily be applied to other types of features.



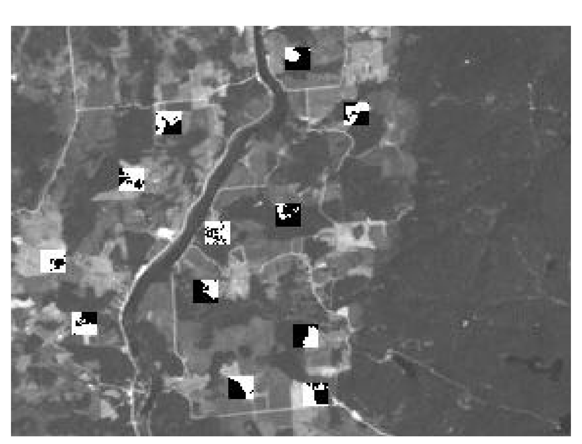
Example of a Landsat-7 image

Step 1: Generation of Training Tiles

A set of tiles representing terrestrial features and non-feature images are extracted by hand in each spectral band. The feature tiles are aligned such that their center corresponds to the center of the feature. The data are enhanced by applying an adaptive threshold (mean of the center region of the tile). In order to normalize the data, the orientation of the inertial axis of intensity values of each segment is computed and the image is rotated to align the segment horizontally.



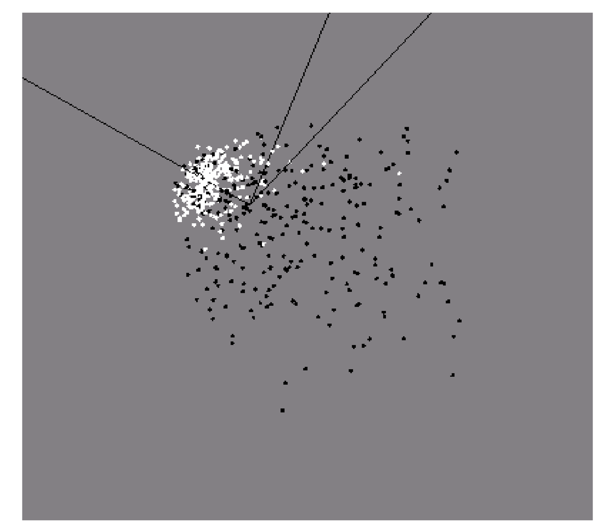
Example of road training tiles



Example of non-road training tiles

Step 2: Construction of an Eigenspace

PCA is then used to build an eigenspace for each band with all the training images, i.e. the feature and "non-feature" tiles. If the training phase is done with appropriate data, the tiles projected back onto the eigenspace should lead to two separated clusters (manifolds) corresponding to the two classes of features.



Projection of the training set onto the 3 first dimensions of the eigenspace (black: non-roads; white: roads)

Step 3: Classification

Tiles of unknown type are projected onto the eigenspace. The Mahalanobis distance between that projection and the mean of the feature cluster is computed. The likelihood of an unknown tile being a feature is then assumed to be inversely proportional to that distance.

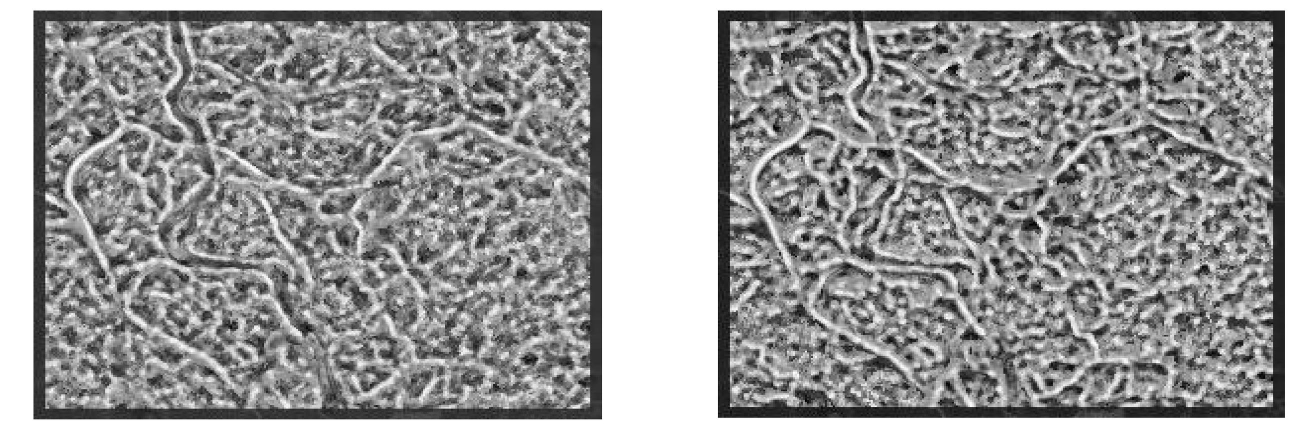
$$\text{likelihood} \propto \left[(\mathbf{x}-\boldsymbol{\mu})^t \Sigma^{-1} (\mathbf{x}-\boldsymbol{\mu})\right]^{-1/2}$$

Step 4: Accumulation of Evidence

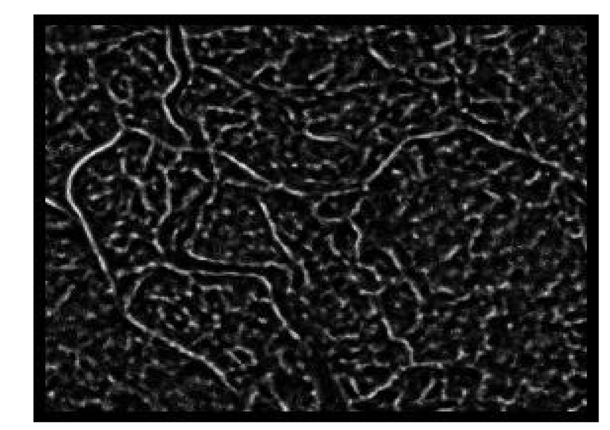
Evidence from several sources of information is accumulated by combining likelihoods across different bands, leading to a more confident assertion. Accumulation is performed by a pixel-wise product of component likelihood measures.

Results

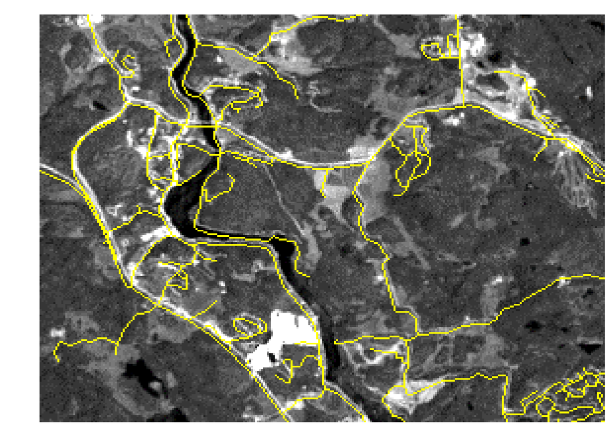
The results of our classification framework are displayed as a likelihood map where white entries are image regions that are more likely to be features.



Likelihood of two different bands



Combination of four likelihood maps



Ground truth

Conclusion

We showed how evidence for different terrestrial features can be computed from multiple spectral bands, and how this evidence can be accumulated, leading to more confident assertions. The framework presented is general, and should not depend on particular image features or imaging modalities.

Future Work

Future work involves the evaluation of other enhancement and invariant operators. Likelihood maps should be further processed to eliminate regions with weak neighborhood support. Experiments on other types of features (buildings, hydro-towers, water bodies, etc.) and on other sources of data (Radarsat, Spot, CDED) are also planned.