Multitemporal Data Registration through Global Matching of Networks of Free-form Curves

Dimitra Vassilaki, Babis Ioannidis, Thanasis Stamos

National Technical University of Athens

Greece

Overview

Introduction

Previous work on Feature-based Matching

Matching Networks of Curves

Identification of Curves Correspondences

Computation of the Common Transformation

Application

Conclusions

Overview

Introduction

Previous work on Feature-based Matching

Matching Networks of Curves

Identification of Curves Correspondences

Computation of the Common Transformation

Application

Conclusions

School of Rural and Surveying Engineering
School of Civil Engineering
National Technical University of Athens

FIG Working Week 2009
Surveyors Key Role in Accelarated Development
Eilat, Israel, 3-8 May, 2009

Introduction: The problem of image registration

Image registration : geometrically match two or more images

Countless Applications:

- multiview analysis
- multitemporal analysis
- multimodal analysis
- scene to model registration
- Computer vision
- Medical imaging
- Photogrammetry & Remote sensing
- Inspection & Quality Control

The 4 Steps of Image Registration:

- feature detection
- feature matching
- mapping function design
- image transformation and resampling

Introduction: Matching Methods

The matching step of the registration procedure can be done:

Area - based methods
- Correlation-like
- Fourier
- Mutual information
- Optimization

Feature - based methods
- Spatial relations
- Invariant descriptors
- Relaxation
- Pyramids and wavelets

Iterative Closest Point Algorithm (ICP):

Featured-based method which uses spatial relations

General purpose method initially intoduced for efficient registration of:
points, curves and surfaces

Well-known for its efficiency for registration of point clouds

Introduction: Why use free-form curves?

A lot of work has been done in the fields of:
- Feature Extraction
- Feature Based Photogrammetry, especially straight lines

Advantages of linear features over points:
- Man made and physical environment is rich of linear features
- Linear features can be detected more reliably
- Matching linear features is more reliable
- Linear features consist a continuous control of information
- The identification of common linear features is more robust in multitemporal registration

Introduction: Proposed Method

The problem : Heterogeneous Data Registration

Networks of 2D free-form curves

global matching

similarity transformation

initial information available

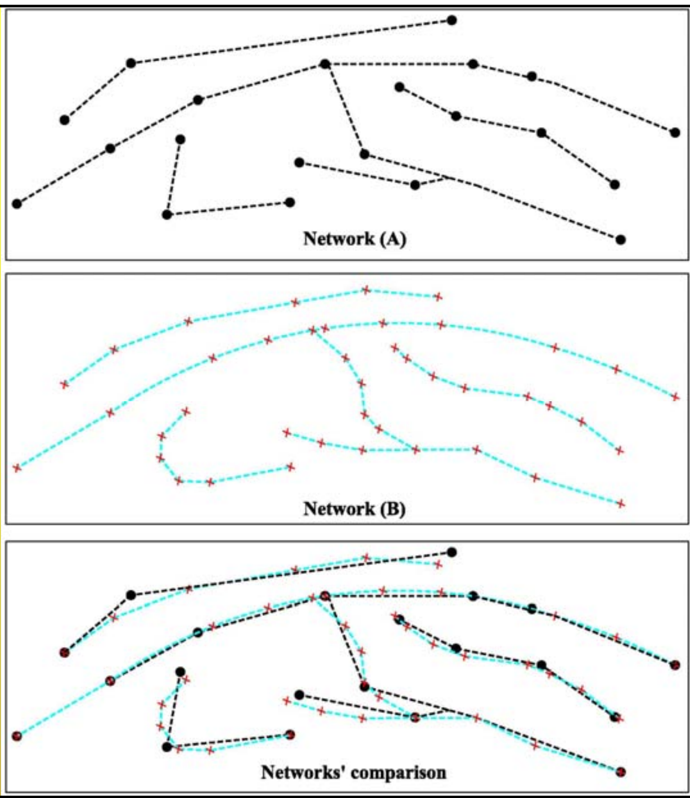
The algorithm : Based on Iterative Closest Point (ICP)

Previous work : Matching of single pairs of curves, with manual pre-alignement and with Automated pre-alignment

This work : Expansion of previous work to Matching Networks of Curves

Why Networks?

A single pair of curves may not represent the datasets in their entirety, as it may be confined to a small region of the datasets.
In most cases multiple pairs of curves must be matched.



Overview

Introduction

Previous work on Feature-based Matching

Matching Networks of Curves

Identification of Curves Correspondences

Computation of the Common Transformation

Application

Conclusions

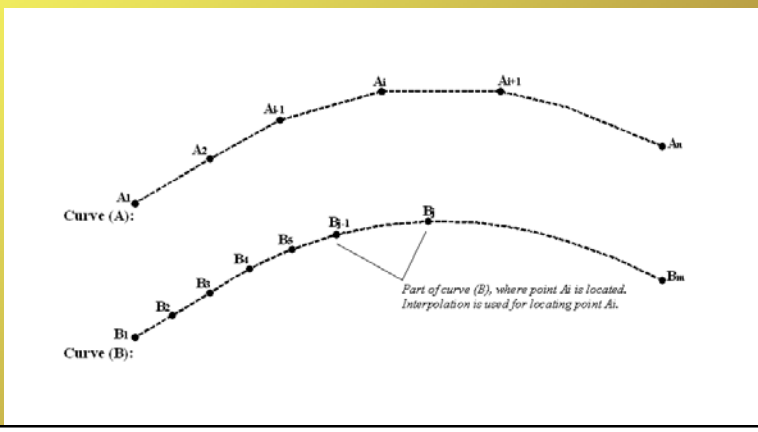
Previous work on Feature-based Matching

Free-form Curves = Natural Curves = Non mathematical curves

Heterogeneous = Extracted from different data with different procedures

Multimodal + multitemporal analysis

Different number and position of nodes



Previous work on Feature-based Matching

An algorithm for ICP-based matching of single pairs of heterogeneous free-form curves has been developed:

i. Compute the closest points between curves
ii. Compute the transformation between the curves using the closest points and Least Squares Method
iii. Apply the transformation to bring the curves closer
iv. Check the threshold.

A novel approach for the computation of closest point pairs between heterogeneous free-form curves matching has been introduced.
It is a Computational Geometry's Proximity Problem:

"Given a node N of a curve (A),
find its minimum distance from another curve (B)"

The ICP algorithm is a very accurate and versatile method, but ...
in order to converge, needs a good first approximation.

This necessity weakens the practicality of the ICP, so ...
a novel method for Automated Pre-alignment of single pairs has been developed

Previous work on Feature-based Matching

Computation of closest points:

- Split of curve B to a large set of consecutive interpolated points, each one very close to its previous and its next point
- Computation of the distances of all these points to a node of curve A
- The point with the least distance is the closest point to the node.

For good results, the distance between two consecutive interpolated points must be very small ⟶ Large set of points & Large computation time

Speeding up the process using the divide and conquer technique:

- The second curve is split to a moderate number of points.
- The closest point to a node on the first curve is located as described.
- The distance between the previous and next point of the closest is split to a finer mesh.
- A new closest point is located.
- The process is repeated until the interpolation distance is small enough.

Previous work on Feature-based Matching

Automated pre-alignment of single pairs

1. calculation of **translation**

A good approximation of the transfer between the 2 curves can be found … as the **vector distance of their centroids**

2. calculation of **scale**

A good approximation of the scale between the 2 curves is … **the ratio of the length of the curves**

3. calculation of **rotation**

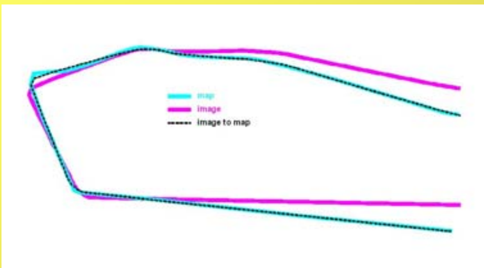
Three different procedures for the calculation of the rotation approximation have been tested:

Rotation approximation using **characteristic points**

Rotation approximation using **average azimuth**

Exhaustive search of the rotation

Previous work on Feature-based Matching



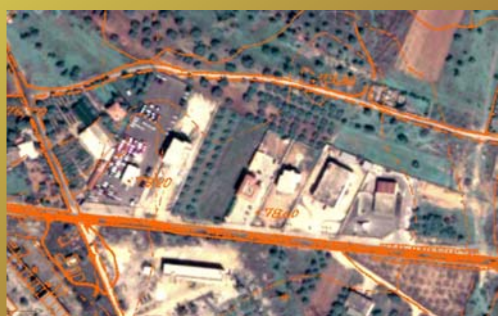
- QuickBird image
- 40 years old map at a scale of 1:5,000

Global matching

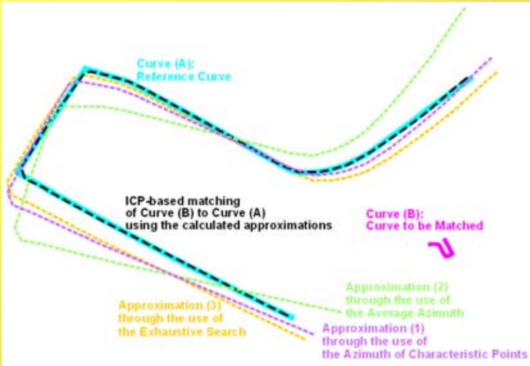
Free-form curves

Single pair of curves

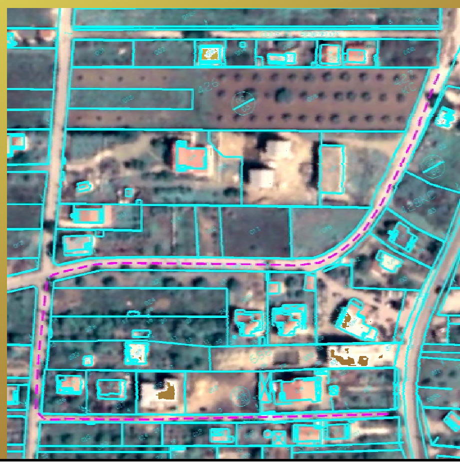
Similarity transformation



Previous work on Feature-based Matching



- QuickBird image
- Vector data at a scale of 1:1,000



Global matching

Free-form curves

Single pair of curves

Similarity transformation

+ Automated Pre-alignment

Overview

Introduction

Previous work Feature-based Matching

Matching Networks of Curves

Identification of Curves Correspondences

Computation of the Common Transformation

Application

Conclusions

Matching Networks of Free-form Curves

Two unique problems, which are not present in single pair curves matching, have to be faced:

a. **Identification of Curves Correspondences,** before the application of the ICP algorithm

It is generally **not known** which of the curves of the first dataset corresponds to which curve of the second dataset.

b. **Computation of the common transformation of all pairs**

All the pairs of curves share a common transformation. Thus it is not possible to match each pair independently, since each matching would produce a different transformation. **All the pairs should be matched simultaneously** in order to produce a single and more accurate transformation.

Overview

Introduction

Previous work on Feature-based Matching

Matching Networks of Curves

Identification of Curves Correspondences

Computation of the Common Transformation

Application

Conclusions

Identification of Curves Correspondences

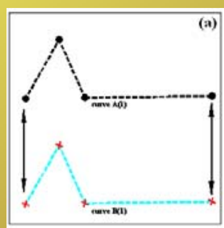
Identification of Curves Correspondences = Similarity Measure

Six different approaches have been tested, for **Automated** Indentification of Curves Correspondence:

1. **End node approach** — Very fast, but ... Not very robust and not general enough
2. **Centroid approach** — Fast and robust but ... not general enough
3. **Length approach** — Fast and robust but ... not general enough
4. **The average distance approach** — Robust and general but... slow
5. **The ICP approach** — Most robust and general but ... the slowest
6. **Hybrid approach** — Robust and Fast **The approach of our choice**

Identification of Curves Correspondences
1. End node approach

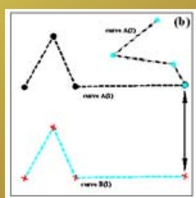
In global matching, the first and last node of each curve have to be homologous:

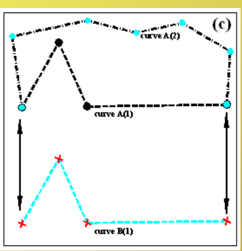


Thus: $\Delta_{AB} = \sqrt{(x_G - x_F)^2 + (y_G - y_F)^2}$ can be evaluated twice

The average of the two (similar) distances can be used as a better metric of the distance between the curves.

This metric is capable to ...
avoid curves which have one common point,
such as when a road forks or
when a road begins where the other ends.





But...
it fails to distinguish between different curves,
in the rare case where two different curves have same ends

The advantage of this approach is that it is very fast since it needs very few

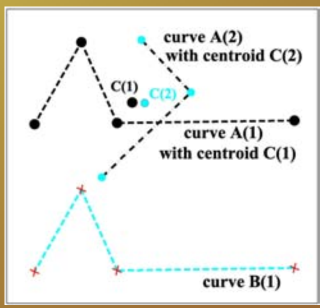
Identification of Curves Correspondences
2. Centroid approach

Assuming global matching, a good metric of the distance of the curves is the distance between the centroids of the two curves:

$$\Delta_{AB} = \sqrt{(\bar{x}_B - \bar{x}_A)^2 + (\bar{y}_B - \bar{y}_A)^2} \qquad \bar{x}_A = \frac{\sum_{j=1}^{N} x_j}{N} \qquad \bar{y}_A = \frac{\sum_{j=1}^{N} y_j}{N}$$

The interpolation of a large number of points implies a large computational cost and heavy memory usage. However, the matching method presented in this paper, computes a large number of interpolation points as a byproduct.

But...
it fails in the rare case when two totally different curves have the same centroid,
such as two intersecting roads.



The advantage of this approach is its robustness and the relatively small number of computations compared to the other approaches.

Identification of Curves Correspondences
3. Length approach

Assuming that the curves are roughly at the same scale, the lengths of two homologous curves must be almost the same.

The absolute difference of the lengths of the curves can be used as metric of the distance of the curves:

$$\Delta_{AB} = |S_B - S_A|$$

But...
it fails when two distinct curves have the same length,
case which is unlikely in the natural environment, but possible in urban areas.

The advantage of this approach is that it is fast
given that the lengths of the curves are calculated once,
the method needs few computations only.

Identification of Curves Correspondences
4. Average distance approach

The first iteration of the ICP approach (no. 5) can be used to find the closest point of every node of the one curve to the other curve.

The average distance of the closest points is used as the metric of the distance between the curves.

$$\Delta_{AB} = \frac{\sum_{j=1}^{N} d_j}{N} \qquad d_j = \sqrt{(x_{Bj} - x_{Aj})^2 + (y_{Bj} - y_{Aj})^2}$$

N is the number of nodes and
x, y are the coordinates of the nodes and their closest points.

Robust and general but slow

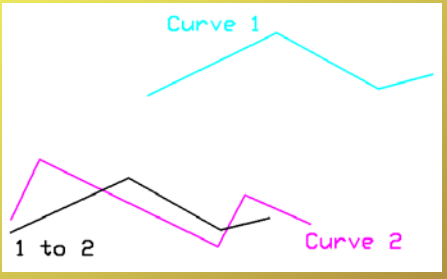
Identification of Curves Correspondences
5. ICP approach

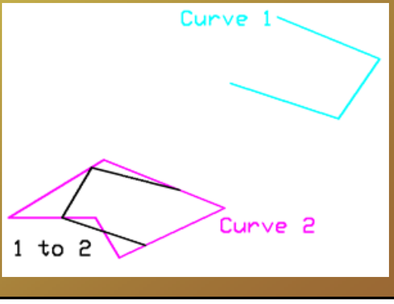
Every curve of the first network is matched with every curve of the second network, using:

- Automated Pre-alignment
- Matching single pairs of free-form curves.

The homologous pair will be the one with the minimum RMS error.

! The developed method is able to match **absolutely different** free-form curves.





Identification of Curves Correspondences
6. Hybrid approach

Compute:

i. the distance between first nodes (d1) "First node approach", **no.1**

ii. the distance between last nodes (d_N) "Last node approach", **no.1**

iii. the distance between centroids (d) "Centroid approach", **no.2**

iv. the absolute difference of the curve lengths "Length approach", **no.3**

The biggest of these four values is used as a metric of the distance of the curves.

$$\Delta_{AB} = \max \begin{Bmatrix} d_1 \\ d_N \\ \bar{d} \\ \Delta S \end{Bmatrix} = \max \begin{Bmatrix} \sqrt{(x_{B1}-x_{A1})^2+(y_{B1}-y_{A1})^2} \\ \sqrt{(x_{BN}-x_{AN})^2+(y_{BN}-y_{AN})^2} \\ \sqrt{(\bar{x}_B-\bar{x}_A)^2+(\bar{y}_B-\bar{y}_A)^2} \\ |S_B-S_A| \end{Bmatrix}$$

It is almost impossible for two distinct curves B and C to have almost identical values of d_1, d_N, d, ΔS with a curve A.

In the unlikely case, the "ICP approach" (**no.5**) can be used to determine which of the two curves is really homologous to A.

Overview

Introduction

Previous work on Feature-based Matching

Matching Networks of Curves

Identification of Curves Correspondences

Computation of the Common Transformation

Application

Conclusions

Computation of the Common Transformation

METHOD 1: ONE STEP SOLUTION **The method of our choice**

Simultaneous ICP-based Matching of all curves

a. For each pair of curves:
   a1. For each node of the curve of the first dataset, determination of its closest point on the curve of the second dataset.

b. Computation of the RMS error of all pairs using the determined closest points of all pairs.

c. Use of the determined closest points of all pairs to compute the parameters of the single transformation with the LSM method.

d. For each pair of curves:
   d1. Transformation of the curve of the second dataset using the transformation parameters.

e. Repetition of steps a, b, c, d until convergence to the minimum error.

Computation of the Common Transformation

METHOD 2: TWO STEPS SOLUTION

- ICP-based matching separately for each pair of curves, for improvement of the pre-alignment
- simultaneous matching of all curves

The "improvement" of the pre-alignment:

- increases the complexity of the method
- it is also slower, as the number of operations is slightly larger for each iteration of LSM.

For each one of the two alternative procedures, the total number of operations depends also on the number of the iterations needed.

The "improvement" of the pre-alignment (**Method 2**) does not reduce dramatically the number of iterations, due to the nonlinear convergence of the ICP algorithm.

Overview

Introduction

Previous work on Feature-based Matching

Matching Networks of Curves

Identification of Curves Correspondences

Computation of the Common Trnasformation

Application

Conclusions

Application: Study area & Data

Data:

- An orthorectified high resolution satellite IKONOS image (pixel size 1m), captured at **2000**
- A medium scale old topographic map

  The original map was in analogue form, at a scale of 1:5,000,
  It was compiled by stereo-restitution of aerial photos,
  taken at **1970**

Purpose: Registration of data using free-from curves matching road centerlines and buildings outlines

Application: Workflow

STEP 1: Map

Manually extraction of the road edges and the buildings‘ outlines
Calculation of the road centerline from the edges, though the use of skeletonization techniques.

STEP 2: Orthoimage

Semi-automatic extraction of the road edges and the buildings' outline, by hand-digitizing the lines appeared on the image after applying Sobel filter.

Calculation of the road centerline from the edges, though the use of skeletonization techniques.

STEP 3: Pre-alignment of the two networks

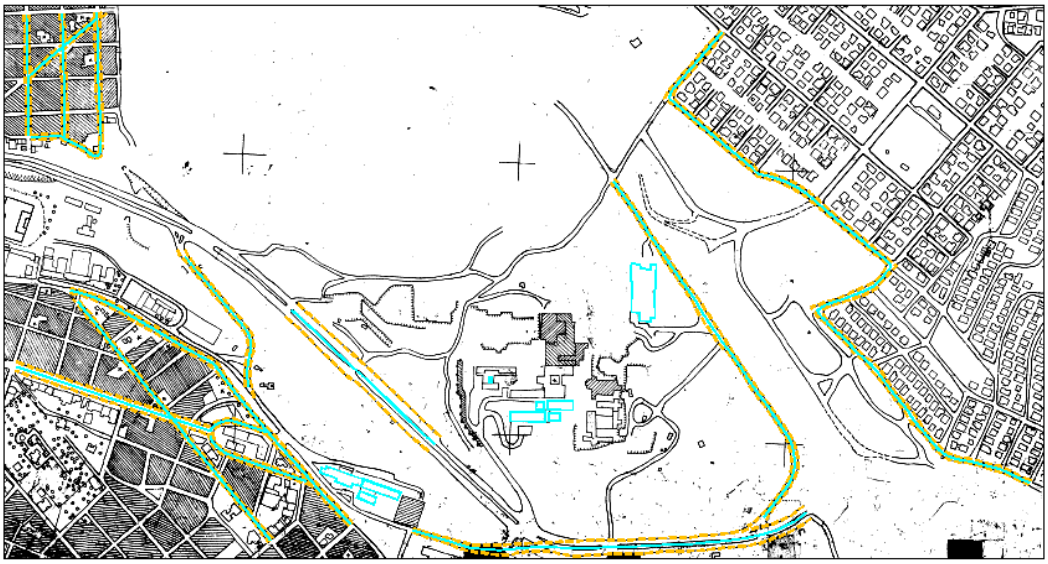
STEP 4: Preliminary registration

by using the selected linear features, which were considered or seemed to be common.

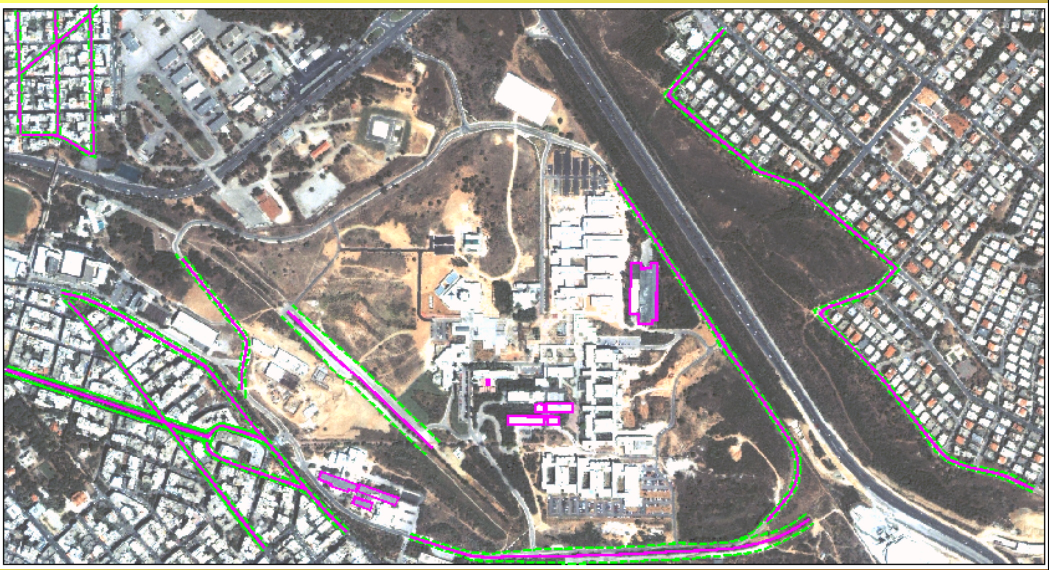
STEP 5: Global Matching of Networks of Free-form Curves

STEP 6: Data registration using the results of the previous step

Application: The map

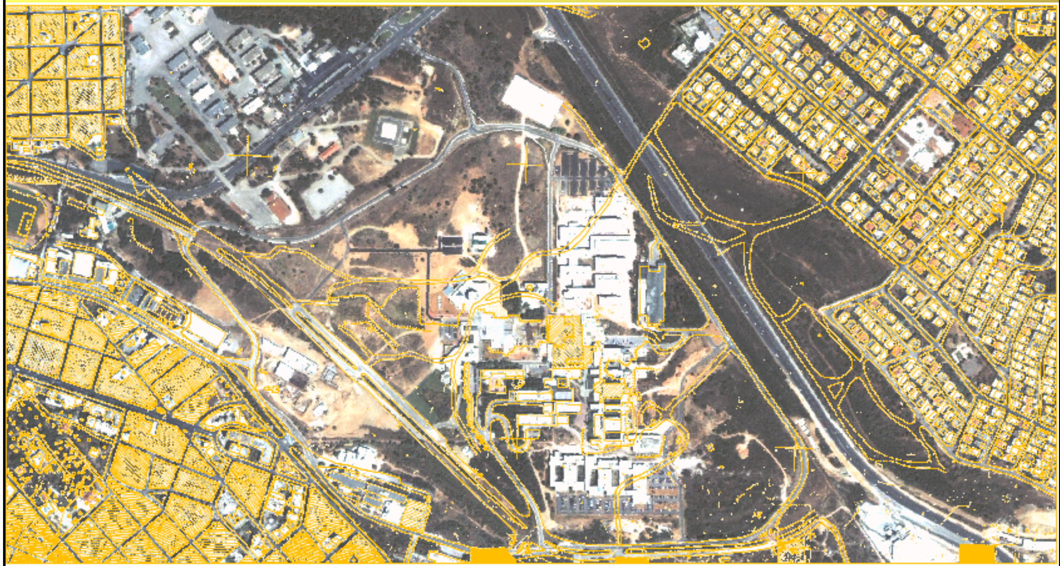


Application: The image



Application: Matching results

Application: Registration results



Overview

Introduction

Previous work on Feature-based Matching

Matching Networks of Curves

Identification of Curves Correspondences

Computation of the Common Transformation

Application

Conclusions

Conclusions

Method for Registration of Heterogeneous data using an ICP-based algorithm for Global Matching of Networks of 2D free-from curves

Two problems, faced:

a. Identification of Curves Correspondences
b. Computation of the common transformation of all pairs

The method is independent to:

- image/data type
- view or time

The method is promising for applications which require image/data registration and:

- can not exploit colour information
- GCPs are not available

Conclusions

Some significant applications of such algorithms are for:

- Georeference of satellite images, with no GCPs

for most areas medium scale topographic maps or orthophotos are available today, which include linear data that remain unchanged

- Georeferencing of non optical images

e.g., radar/SAR sensors; in such cases finding GCPs is not an easy issue, as for images derived from optical sensors

- Orientation of old aerial photos

when the area has changed a lot, so it becomes difficult to accurately locate GCPs

e.g., for aerial photos of 1945 or 1960, which are used in Greece to define the forest land