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

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Key words: Registration, Matching, Iterative Closest Point algorithm, Change detection

SUMMARY

In recent years the frequency of geospatial data collection (optical, SAR, lidar, hyperspectral) has been increased and the methods for surveying and mapping of earth's surface have been improved technically and economically. Consequently, a large volume of multitemporal data is available, which contains information appropriate for a number of applications, such as temporal change detection, coastline or urban development monitoring, deforestation, etc. For the good use of these data several point-based or feature-based registration techniques have been developed. Recently linear features are gaining interest over points in registration procedures, because man made environment is rich of linear features, linear features can be detected more easily and more reliably than points and matching of linear features is often more reliable than point matching.

In this paper a method for multitemporal heterogeneous data registration through global matching of networks of free-from curves based on the Iterative Closest Point (ICP) algorithm is presented. The correspondence of each curve in one dataset with a curve in the other dataset must be established before the application of the ICP algorithm. Six different approaches have been tested; finally, a hybrid method is proposed, which includes the calculation of various values as metrics of the distance of the curves in the two datasets. Next, it is necessary to match all the available pairs of curves simultaneously, because the curves share a common transformation; thus it is not possible to match each pair independently, since each matching would produce a different transformation. Alternative techniques have been tested for the minimization of the necessary total computational time, e.g., by automate improvement of the pre-alignment.

The performance of the proposed strategy was tested with simulation and real data. The registration of an orthorectified high resolution satellite image with an old medium scale topographic map is given as an application. The procedure followed is described and the results are presented, which are especially promising, as the registration accuracy is of the same order with the accuracies of the data.

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1. INTRODUCTION

Multitemporal data registration, or accurate registration of images/data taken at different times, is a prerequisite procedure of significant importance in many applications concerning temporal change detection (Townshend et al, 1992; Dai, 1998), such as land cover change detection, coastline monitoring, deforestation, urbanization, informal settlements detection, etc. A variety of change detection algorithms may be used (Chen et al, 2003); image differencing (Casteli et al, 1998), principal component analysis (Mas, 1999), change vector analysis (Lambin & Strahler, 1994), Markov random fields (Kasetkasem & Varshney, 2002), neural networks (Liu & Lathrop, 2002) are some of the tools that have been used.

The problem becomes more complicated when the geospatial data, that should be registered, are derived from different techniques and have various accuracies and resolutions. In recent years, the use of new instruments for surveying and mapping, such as SAR, LIDAR, GPS, and the application of novel techniques for the extraction of various products, has created the need for development of multitemporal heterogeneous data registration techniques.

In this paper, a method for multitemporal data registration through global matching of networks of free-form curves is presented. The approach is based on the Feature Based Photogrammetry's (FBP) principle, which states that linear features exhibit certain advantages over the classical point based approach for the orientation processes (Kubik, 1998; Zalmanson, 2000; Changno & Bethel, 2004; Schenk, 2004):

- Man made and physical environment is rich of linear features (roads, pipelines, coastlines)
- 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. Experience tells that identification of common nodes is difficult and rare, and when a common pair is found (for example a crossroad), their exact relative position is often questionable.

The proposed approach has also taken into account the advancement of feature extraction techniques from various kind of imagery and data (optical, radar, hyperspectral, lidar etc) (Barzohar & Cooper, 1996; Katartzis et al, 2001; Jeon et al, 2002; Tupin et al, 2002; Changno & Bethel, 2004). It is based on Iterative Closest Point (ICP) algorithm (Besl & McKay, 1992; Zhang, 1994) with a divide-and-conquer approach for the computation of the closest points pairs (Vassilaki et al, 2008a). The identification of the features correspondences and the simultaneous matching of all the pairs of curves are two problems, which are not present in single pair curves matching and need further investigation.

2. MATCHING NETWORKS OF CURVES

In multitemporal data processing linear features are extracted with different processes from different kind of data. Thus, the nodes which define the, generally curved, linear features may vary wildly. The position, the density and even the number of the nodes are generally different in the two curves being matched (Figure 1). Direct matching of the nodes is clearly impossible.

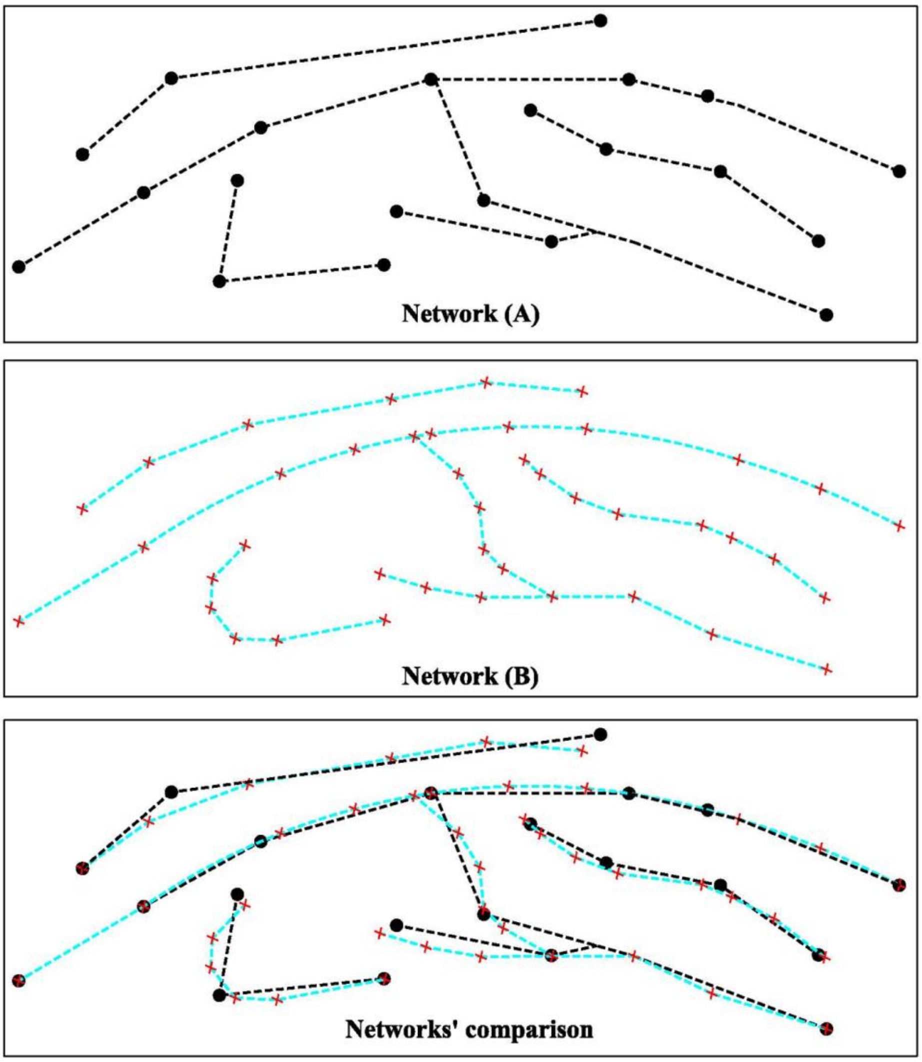

Figure 1. The problem of global matching of networks of heterogeneous curves

In this work, curves are considered as independent collections of consecutive nodes which are joined with straight line segments, or some other interpolation function, such as cubic splines. In any case the original measurements, or information, is in the form of 2D or 3D node coordinates: $N_i(x_i, y_i)$, $N_i(x_i, y_i, z_i)$. This representation of curves is preferred, because the curves to be matched are free-form (natural) curves which represent objects of unknown geometry that appear in physical and man-made environment, such as road centerlines and coastlines. Alternatively if in some cases, such as highway centerlines, the curves are of known mathematical form, the “interpolation” is done with the exact mathematical formula.

The linear features (curves) that are identified in two heterogeneous multitemporal datasets of the same area and are going to be matched, are generally non-continuous. The larger curve could be chosen and the match of the datasets could be based on the matching of a single pair of curves. This is certainly possible and it often leads to sufficient accuracy (e.g., Vassilaki et al, 2008b). However one 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. Two unique problems, which are not present in single pair curves matching, have to be faced:

a. It is generally not known which of the curves of the first dataset corresponds to which curve of the second dataset. Thus the correspondences of the curves must be established before application of the ICP algorithm.
b. 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.

3. IDENTIFICATION OF CURVES CORRESPONDENCES

In order to identify the curves correspondences, it is assumed that the two datasets are initially pre-aligned. This is not a limitation of the proposed method, as the pre-alignment is a precondition for the convergence of the ICP algorithm (Gruen & Akca, 2004). With this assumption the correspondences are easy to identify. A curve of the first dataset corresponds to the curve of the other dataset which is “closest” to it. However, the definition of “closest” is ambiguous for a curve which may span many other curves (Figure 1). Different nodes of the same curve may be closest to nodes of different curves. Clearly the “closeness” must refer to the curve as a whole.

Six different approaches haves been tested in this research:
1. End node approach
2. Centroid approach
3. Length approach
4. The average distance approach
5. The ICP approach
6. Hybrid approach.

Each approach uses a different metric of the “distance” of two arbitrary curves. The pair of curves which have the least metric are homologous. This means that a curve of the first dataset is compared to every curve to the second dataset (exhaustive search), which implies an execution time of $O(n^2)$ (Gruen et Akca, 2004), where n is the number of the different curves.

Quadratic execution time is prohibitive for large n, but the number of individual curves is rather small, usually less than twenty and very rarely greater than a hundred. These numbers are within the capabilities of modern computers.

3.1 End node approach

Let F be a characteristic point on curve A and let G be the same characteristic point in curve B. Then the distance between the points can be used as a (not very good) metric of the distance of the curves:

$$\Delta_{AB} = \sqrt{(x_G - x_F)^2 + (y_G - y_F)^2} \qquad \text{(Eq. 1)}$$

In global matching, the first and last node of each curve have to be homologous (Figure 2a) and thus Eq. 1 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 (Figure 2b). However it fails to distinguish between different curves, in the rare case where two different curves have the same ends (Figure 2c). The advantage of this approach is that it is very fast since it needs very few computations.

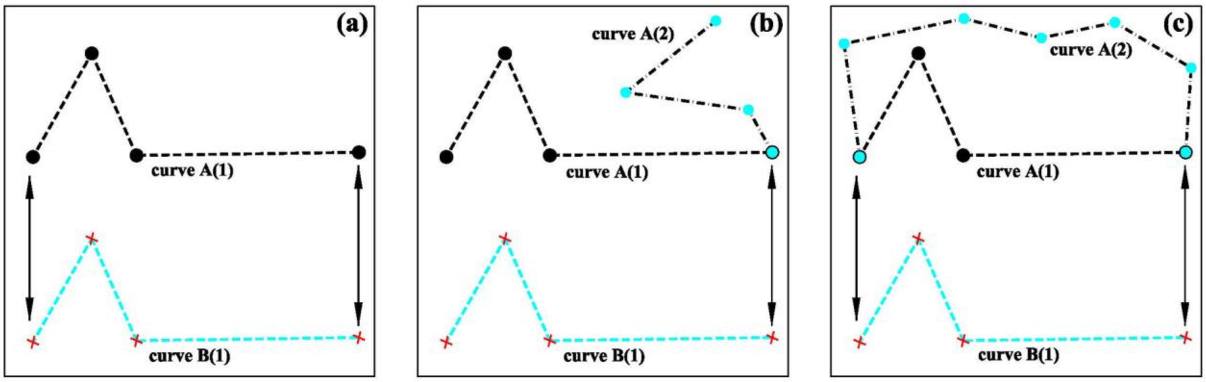

Figure 2. (a) Homologous end nodes, (b) common end nodes, (c) common start and end nodes

3.2 Centroid approach

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

$$\Delta_{AB} = \sqrt{(\bar{x}_B - \bar{x}_A)^2 + (\bar{y}_B - \bar{y}_A)^2}, \text{ where}$$

$$\bar{x}_A = \frac{\int_{S_A} x(s)ds}{\int_{S_A} ds}, \quad \bar{y}_A = \frac{\int_{S_A} x(s)ds}{\int_{S_A} ds}, \quad \bar{x}_B = \frac{\int_{S_B} x(s)ds}{\int_{S_B} ds}, \quad \bar{y}_B = \frac{\int_{S_B} x(s)ds}{\int_{S_B} ds} \qquad \text{(Eq. 2)}$$

S_A, S_B are the lengths of the curves, s is the integration variable which spans each curve, and x(s), y(s) are the function of the coordinates with respect to s.

The centroids are quite insensitive to random errors in the nodes of each curve, as the errors tend to cancel out each other. Thus the centroid is the best single point representation of a curve. If the interpolation between the nodes is linear then the integrals can be computed analytically. However, if the interpolation between the nodes is nonlinear, then analytic integration of Eq. 2 is difficult if not impossible. Numerical integration using a large number of equidistant interpolated points can be done as:

$$\bar{x}_A = \frac{\sum_{j=1}^{N} x_j}{N}, \quad \bar{y}_A = \frac{\sum_{j=1}^{N} y_j}{N} \qquad \text{(Eq. 3)}$$

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, which can be exploited for the evaluation of Eq. 3. Thus the computational cost of Eq. 3 is negligible. As an additional bonus, Eq. 3 is independent to the interpolation used and thus it is very general. However it fails in the rare case when two totally different curves have the same centroid, such as two intersecting roads (Figure 3). The advantage of this approach is its robustness and the relatively small number of computations compared to the next approaches.

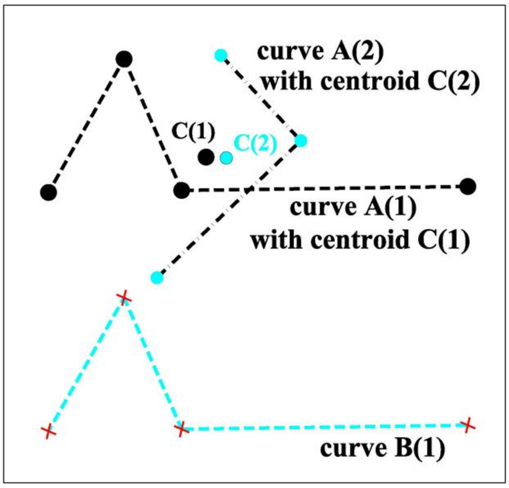

Figure 3. Different curves with same centroid

3.3 Length approach

Assuming that the curves are roughly at the same scale, the lengths of two homologous curves must be almost the same. Then the absolute difference of the lengths of the curves can be used as metric of the distance of the curves:

$$\Delta_{AB} = \left| S_B - S_A \right| \qquad \text{(Eq. 4)}$$

This approach obviously 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.

3.4 The average distance approach

The first iteration of the ICP algorithm can be used to find the closest point of every node of a curve to the other curve. The average distance of the closest points is used as the metric of the distance between the curves.

$$\Delta_{\mathrm{AB}} = \frac{\sum_{j=1}^{N} d_j}{N} \qquad \text{(Eq. 5)}$$

where: $d_j = \sqrt{(x_{Bj} - x_{Aj})^2 + (y_{Bj} - y_{Aj})^2}$,

N is the number of nodes and

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

In order to accommodate for non-uniform density of nodes (Figure 4a) and assuming linear interpolation of the distance between nodes:

$$\Delta_{\mathrm{AB}} = \frac{\sum_{j=1}^{N-1} \frac{(d_j + d_{j+1})}{2} s_j}{\sum_{j=1}^{N-1} s_j} \qquad \text{(Eq. 6)}$$

where $s_j = \sqrt{(x_{A(j+1)} - x_{Aj})^2 + (y_{A(j+1)} - y_{Aj})^2}$ is the distance of consecutive nodes.

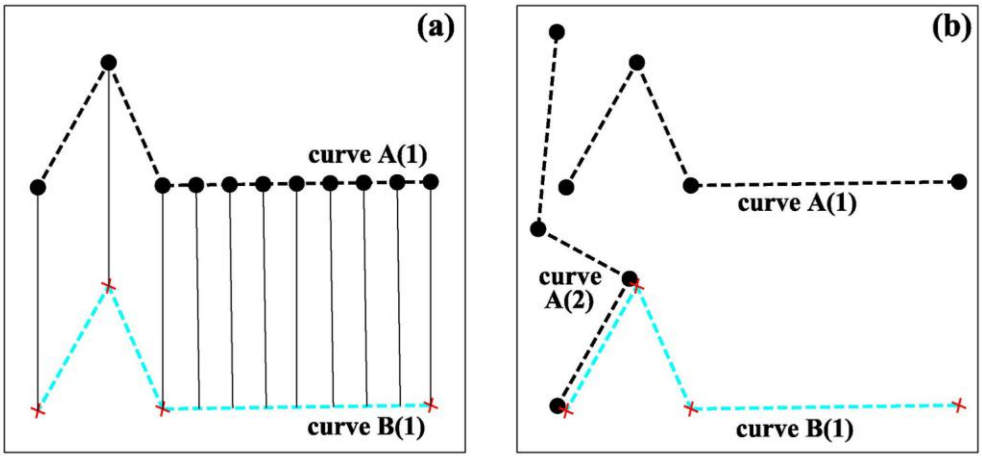

Figure 4. (a) Non-uniform density of nodes,
(b) Not homologous curves which have a short identical part

It must also be ensured that the common part of the curves, where the ICP finds closest points, is big enough to be reliable. Otherwise, if a small part of the curves is identical, the algorithm will erroneously accept them as homologous (Figure 4b). However, experimentation has shown that ensuring a large common part, for example 75%, is too restrictive and the correspondence of many pairs is not identified, even with a small rotation angle. If the percentage is lowered, the original danger remains.

The solution is to multiply the metric by a corrective coefficient, which is big when the common part is small and close to unity if the common part is big. The inverted ratio of the common length to the length of one of the curves is the obvious choice, but experience showed this to be somewhat insensitive to small common part. Thus the square of the inverted ratio is used:

$$\Delta^{*}_{AB} = \Delta_{\mathrm{AB}} \left[\frac{S_A}{\sum_{j=1}^{N-1} s_j} \right]^2 \qquad \text{(Eq. 7)}$$

where S_A is the length of the first curve. The power of 2 ensures that for small common parts, for example 10%, the error will be multiplied by 100, so that the algorithm will choose a curve with bigger common part as homologous, if there is one. Otherwise, the curve with the small common part will be the homologous one, and small common part would be probably due to poor pre-alignment.

3.5 The ICP approach

The full ICP algorithm can be used to match each curve of the first dataset to every curve of the second dataset. For many pairs the ICP will not converge, while for others the final RMS error will be large. The real homologous pair will be the one with the minimum RMS error.

The ICP algorithm for a single pair of curves (A and B) consists of four steps which are repeated until convergence within a tolerance (Besl and McKay, 1992; Zhang, 1994):

1. Compute the closest points between curves
2. Compute the transformation between the curves using the closest points and Least Squares Method
3. Apply the transformation to bring the curves closer
4. Check the threshold.

In order to find the closest points, curve A is split to a large set of consecutive interpolated points, each one very close to its previous and its next point. Then, the distances of all these points to a node of curve A may be computed, and the point with the least distance is the closest point to the node. For this brute method to produce good results, the distance between two consecutive interpolated points must be very small, which leads to a large set of points and large computation time. It is, however, relatively easy to speed 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. Then the distance between the previous and next point of the closest is split to a finer mesh and a new closest point is located. The process is repeated until the interpolation distance is small enough.

The ICP approach is very robust, but it has the disadvantage that it is computationally very intensive.

3.6 Hybrid approach

The ICP approach is the best of the first four approaches presented above, because it leaves no doubt about the result. However it is also very time consuming and it would be advantageous to avoid it, or at least to use it as little as possible. Thus a hybrid approach is proposed. The distance between three characteristic homologous points is computed: the first node, the last node and the centroid (first and second approach). The absolute difference of the curve lengths is also computed (third approach). The biggest of these four values is used as a metric of the distance of the curves.

$$\Delta_{AB} = \max\begin{Bmatrix} d_1 \\ d_N \\ \bar{d} \\ \Delta S \end{Bmatrix} = \max\begin{Bmatrix} \sqrt{(x_{B1}-x_{A1})^2+(y_{B1}-y_{A1})^2} \\ \sqrt{(x_{BN}-x_{AN})^2+(y_{BN}-y_{AN})^2} \\ \sqrt{(\bar{x}_B-\bar{x}_A)^2+(\bar{y}_B-\bar{y}_A)^2} \\ |S_B-S_A| \end{Bmatrix} \qquad \text{(Eq. 8)}$$

It is almost impossible that two distinct curves B and C exist, for which the values of d_1 , d_N, $\bar{d}$, ΔS with curve A are identical. However in the unlikely case that it is so, the ICP approach can be used to determine which of the two curves is really homologous to A.

4. COMMON TRANSFORMATION

The ICP for a single pair of corresponding curves between the two datasets, computes the closest points and the transformation using all the available data (Vassilaki et al, 2008a). Likewise, when there are multiple pairs of corresponding curves, the transformation is common to all pairs and it is computed using all the data available (all the pairs). However, the closest points are not computed using the data of all the pairs, since it would be obviously an error to find closest points between unrelated curves. The computation of closest points is done independently for each pair of curves. Then, the closest points of all the pairs of curves are used to determine the parameters of a single transformation. The modified ICP algorithm for multiple pairs is summarized in Table 5.

a. For each pair of curves do: *a1. For each node of the curve of the first dataset, determine its closest point on the curve of the second dataset.* *b. Compute the RMS error of all pairs using the determined closest points of all pairs.* *c. Use 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 do:* *d1. Transform the curve of the second dataset using the transformation parameters.* *e. Repeat steps a, b, c, d until convergence to the minimum error.*

Table 5. ICP for global matching networks of free-form curves

4.1 Computational aspects

The use of multiple pairs of curves for the ICP increases the robustness of ICP. If the pre-alignment is poor, then the ICP does not converge. However, it is conceivable that the ICP converges for one or two of the many pairs of corresponding curves, where the pre-alignment is a little better by chance. This partial transformation, which is a good approximation to the global transformation, can be used to transform the rest of the pairs. This essentially improves the pre-alignment, making global ICP convergence possible.

The matching of multiple pairs of curves puts additional numerical burden to the ICP algorithm, which is already computational intensive. So, it is important to minimize the iterations needed by the multiple curves matching, improving the pre-alignment. This could be achieved by performing the ICP individually to each one of the pairs at first, and then using the found closest points to initiate the matching of multiple pairs. In essence we would have less multiple ICP iterations at the expense of more individual ICP iterations.

Unfortunately this actually increases the computational cost and the computational time. For the analysis of the computations M curves, N nodes on each curve on the average, P parameters of the transformation, J dimensions are assumed.

For one individual ICP iteration, the dimensions of the matrices involved in Least Square Method (LSM) adjustment: $[A][X]=[B]$, are respectively: $NJ \times P,\quad P \times 1,\quad NJ \times 1$
Since M individuals ICP applications are done, M matrices $[A]$ and $[B]$ are created.

On the other hand, the dimensions of the matrices for one iteration of the global ICP, are respectively: $MNJ \times P,\quad P \times 1,\quad MNJ \times 1$
Thus the computational cost for creating these matrices is equivalent for both approaches.

The solution of the matrix equations with LSM is typically done as:

$$[A^T][A][X] = [A^T][B] \Rightarrow [N][X] = [u]$$

where the dimensions of the final matrices $[N],[u]$ are respectively: $P \times P, P \times 1$

The number of arithmetic operations needed to perform the two matrix multiplications and the solution of the linear system of equations for one individual ICP are respectively (Press et al., 1992): $P^2 NJ$, PNJ, $P^3/6$. Since M individuals ICP applications are done, the total number of arithmetic operations is:

$$M(P^2NJ + PNJ + P^3/6) = P^2MNJ + PMNJ + MP^3/6 \qquad \text{(Eq. 9)}$$

In the case of global ICP, the number of the arithmetic operations is:

$$P^2MNJ + PMNJ + P^3/6 \qquad \text{(Eq. 10)}$$

As it can be seen, the "improvement" of the pre-alignment not only increases the complexity of the method, but it is also (slightly) slower, as the number of operations is slightly less for the multiple ICP. Obviously, for each one of the two alternative procedures, the total number of operations depends also on the number of the iterations needed.

5. APPLICATION

The operation and the results of the above described alternative approaches and techniques for curves correspondence and determination of transformation parameters have been tested through the development of an in-house software. The applicability, the efficiency and the accuracies of the results have been checked by using simulation and real data.

By example, an application of the proposed method in the broader area of a university campus is given below. The data used include:

- an orthorectified high resolution satellite image. It is an IKONOS image, with a pixel size of 1m, captured at 2000 and
- a medium scale old topographic map; the original map was in analogue form at a scale of 1:5,000 and it was compiled by stereo-restitution of aerial photos, taken at 1970 (30 years before the acquisition of the satellite image).

The study area exhibits wide temporal changes, as the most buildings of the campus and the road network were build after 1970. The available map and the image exhibit few common features. The most of these common features are roads. Some buildings can also be identified on both data (Figure 6).

The registration of the two data was based on road centerlines and buildings outlines. For the map, the road edges extraction and the buildings' outlines was done manually, by digitizing the lines appeared on the map. Then the road centerline was calculated from the edges, though the use of skeletonization techniques (Figure 6-top). For the orthoimage, the road edges and the buildings' outlines extraction were done semi-automatically, by hand-digitizing the lines appeared on the image after applying Sobel filter. Then the road centerline was calculated from the edges, though the use of skeletonization techniques (Figure 6-bottom). A preliminary registration was made by using a great number of linear features, which might be considered or seemed to be common. The selection of the features that were used finally for the application was made according to their statistical values in this solution.

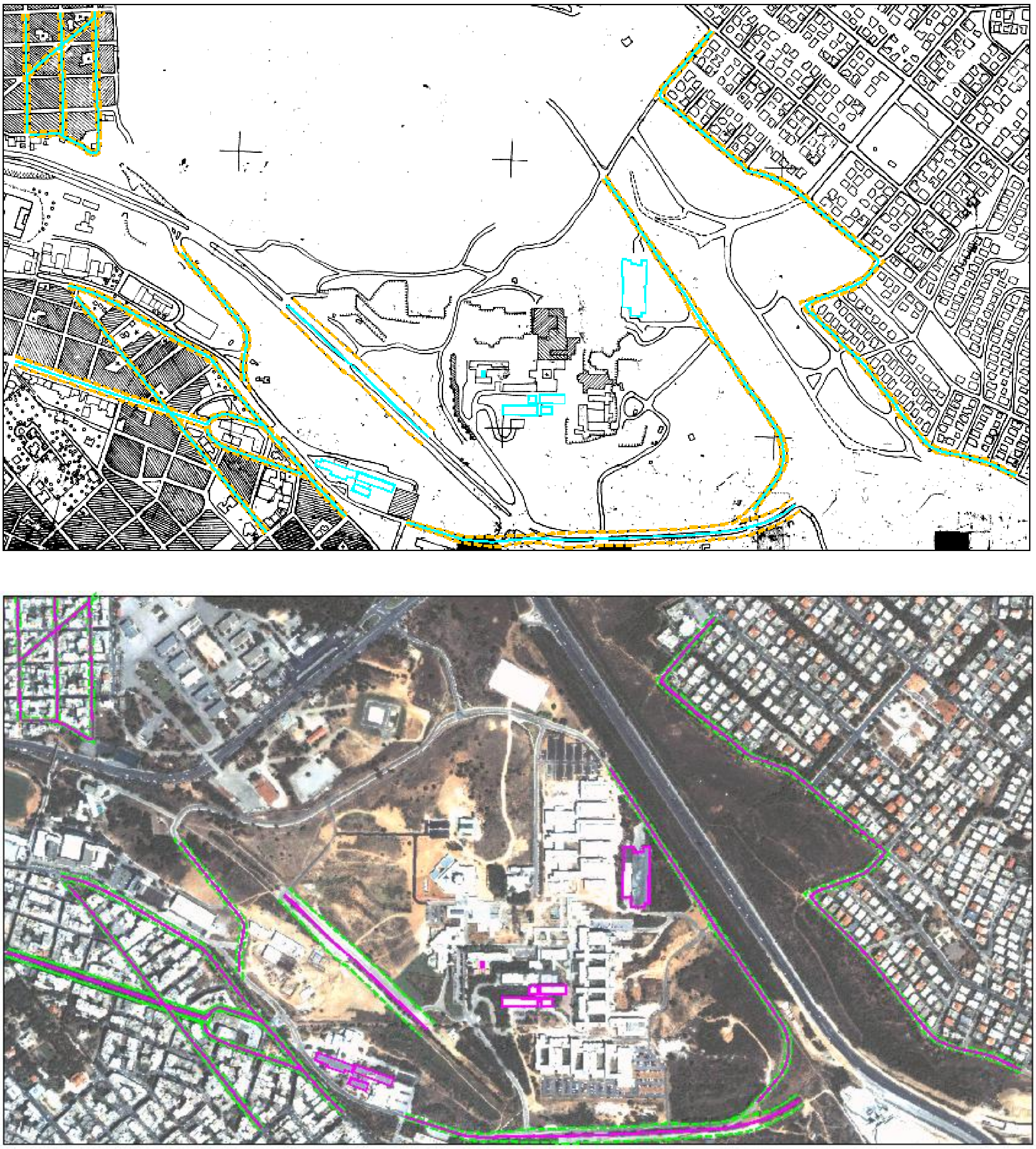

Figure 6. Study area with the linear features used for the registration:
Map restituted in 1970 (top) - IKONOS satellite image captured in 2000 (bottom)

Since the extraction of road centerline was done independently for the map and the satellite image, it was necessary to have a good initial estimation for the ICP algorithm. This information was acquired by using the same reference system for the map and for the image processing. Practically that means that before the extraction of curves and the registration, the map and the image have to be roughly pre-aligned. Otherwise ICP does not converge. A network of 22 free-form curves were located and used for the registration, which include roads' centerlines and building outlines. In Figure 7 the reference network of curves, which are extracted from the map, appears with cyan color; the network to be matched, which is consisted of curves from the satellite image, appears with magenta color. For the identification of curves correspondence the hybrid approach was applied, which was proved to give the best results. The correspondence of the 22 pairs of curves was absolutely successful (Figure 8).

The matching procedure of the corresponding curves was made by using the ICP algorithm; the 2D similarity transformation was used as a mathematical model for the transformation. Both techniques described above were applied:

- the one-step solution, using simultaneous ICP-based matching of all curves
- the two-steps solution; initially ICP-based matching separately for each pair of curves, for improvement of the pre-alignment, and, afterwards, simultaneous matching of all curves.

The final results were exactly the same in both techniques. The matched network of curves appears with black dashed line in Figure 7. As it can be seen the centerlines are virtually indistinguishable. The final rms of the registration was 1.60 m, which is an excellent result; it is of the same order with the accuracy of the old topographic map.

Comparing the two techniques the following can be derived:

- The ICP algorithm for simultaneous matching of all curves converged in 23 iterations. The root mean square error (rms) of the first iteration was 27.11 m and the rms of the last iteration was 1.60 m. In total (23x22=) 506 ICP iterations were necessary for the matching of all the 22 pairs of curves.
- In the case that improvement of the pre-alignment was applied, the convergence of the simultaneous matching was made in 20 iterations, with rms of the first iteration 12.48 m and rms of the last iteration 1.60 m. However, the improvement of the pre-alignment had already been achieved through 3-50 iterations of the single pair ICP algorithm; in total 527 iterations were needed for the matching of 21 curves, as for one curve the ICP did not converge, probably due to poor initial approximation (in the procedure of simultaneous matching all 22 curves participated). So, for the whole process (527+440=) 967 iterations of ICP algorithm were needed, that is almost double the number of those in the previous technique.

Consequently, it is derived that the adjustment with simultaneous matching of all curves is preferable, as long as there are good initial approximations so that the ICP algorithm will converge.

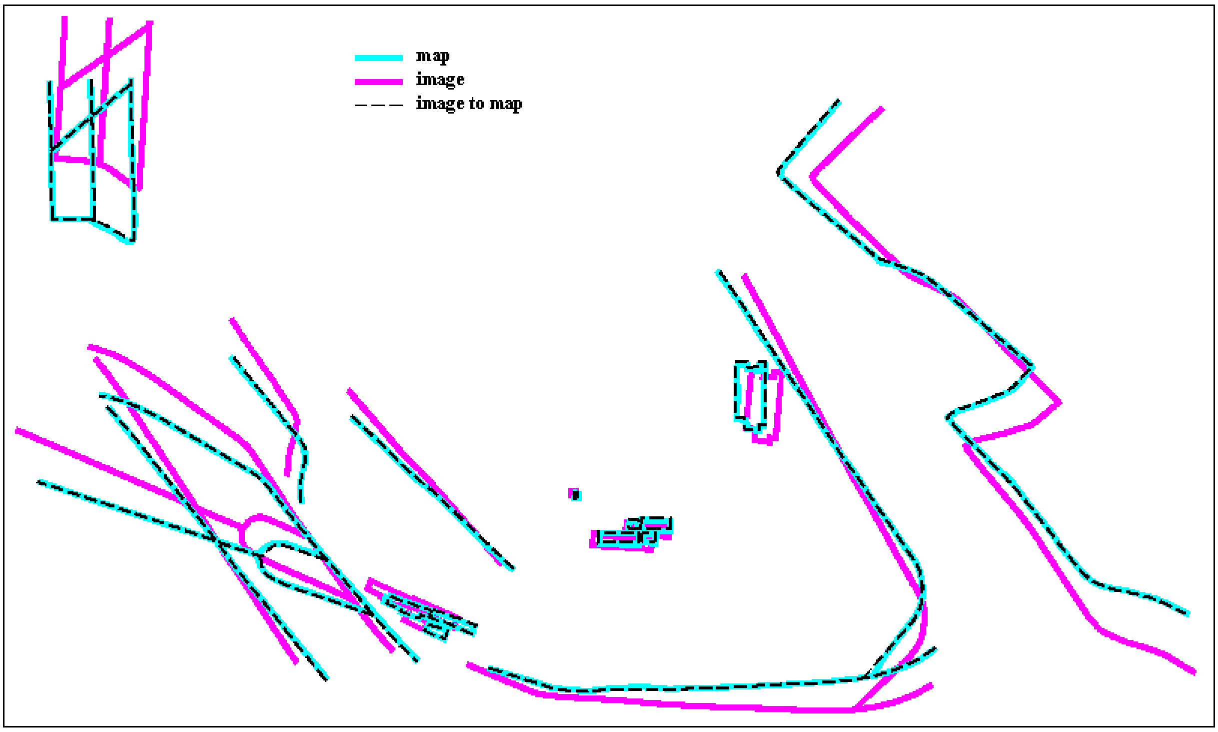

Figure 7. Registration using linear features: pre-aligned data and results

Figure 8. Registration results: Recent satellite image registered to 30 years old map

6. CONCLUSIONS

A new method for multitemporal data registration through global matching of networks of free-from curves is presented. In recent years the development of new sources and techniques for geospatial data collection (satellite data, GPS, Lidar, etc) have led to a great supply of various heterogeneous data (optical, radar, lidar, hyperspectral), which can be used for updating of old maps, change detection, monitoring and other applications. So, the development of procedures for heterogeneous data registration becomes necessary. The proposed method is based on the ICP algorithm and it is independent to data type (image, vector, B/W, color), view or time difference; it can be used in conjunction with existing maps and GIS. The existence of GCPs is not necessary, nor even the location of homologue points in the datasets; data registration is made by using linear features, which can be detected and matched more reliably.

The application of the method in simulation and heterogeneous real data, gave promising results. The use of network of curves, and not of individual pairs of curves, has improved the accuracy of registration; the registration accuracy is of the same order with the accuracies of data. Various alternative techniques were tried in order to minimize the computational time for the ICP algorithm solution. The use of parallel processing techniques may constitute an interested field for future research.

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