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Towards Hybrid Conflation of Spatial Databases: A Review

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ABSTRACT: *Data conflation scenarios play a central role in many parts of recent Geographic Information Systems (GIS), such as geospatial data visualization, incremental updates of databases and disaster evaluation. The main focus of conflation is to derive treasured information based on the contrast of multiple and hybrid spatial data bases, in vector and raster format and of similar or varied nature. This paper analyses the state of art of hybrid conflation and feature similarities. In more detail, the most significant improvements of hybrid conflation between high resolution satellite data in raster format and vectorial network data, representing spatial databases is described.*

KEYWORDS -*Feature correspondence, conflation, de-conflation, existing geospatial databases, density of spatial data conflation, ICP algorithm, Gauss-Helmert model.*

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I. INTRODUCTION

The significance of spatial data in juxtaposition with everyday life and in addition to the rapid development of a modern society using suitable, simple, cost-effective geo-databases and geo-referenced raster images is apparently foreseeable. Different characteristics of modern GIS exploration and development, such as spatial data validation and integration are being used increasingly in road database updates and navigations. Generally, the integration of geo-databases and images is an important issue. The standardized incorporation of thoroughfare databases (street maps in vector format) and very high-resolution (VHR) imagery (in raster data format) may serve as a decent sample to describe the classic problem of mismatch between homogeneous features in a road and image database, which could result from up to 200-meter distances[1]. Feature imbalances between the two data set sources are caused by many factors, such as different resolutions or scales, inaccurate camera models, projection errors, different data acquisition times, and different data suppliers[2]. The misalignments are not systematic but cannot be corrected by a standardized transfer function. The method of spatial data conflation is therefore essential to combine multiple and hybrid datasets. Equivalently geometric, topologic, and semantic features are central issues in the process of conflation [3]. Once coating two inhomogeneous road datasets defining the same region, the homologous road objects may divulge four unalike forms of offsets [4]:

(1) Coincidence.
(2) Intersection.
(3) Disjunction.
(4) Feature inconsistency.

However, there are useful map clipping issues, which are slightly offset for a specific purpose from the original road data. But misalignments may arise as a result of severe compensation during image enlargement and resolution changes. In Sudan we face the problems of mismatching road data bases and VHR satellite date quite often, as this might also occur in other developing countries. Therefore, we try to review the methods of hybrid conflation to be applied for incremental updates of Sudanese road databases.

To answer the question that revolves in the mind of the readers: Why is this research targeting Sudan and no other countries? The answer should include a genuine personal reason and then come to the major reasons, that the lack of basic infrastructures and services in this country is mainly caused by the lack of reliable databases. By doing such a study we introduce an invitation to scholars and activists in the field of GIS to pay attention to Sudan and that this country needs assistance.

The contents of this review paper are as follows: After some introductory remarks (**I**) we present an overview for the concept of geo-data conflation (section **II**). Section **III** briefly summarizes the necessary feature matching problem, followed by an overview of adequate algorithms to overcome this problem (section **IV**). The notion of de-conflation is discussed in section **V** and section **VI** comprises a state-of-the-art of spatial conflation. As there are still some problems to solve, we will discuss the spatial conflation complexity in section

VII. Datasets used in the experiment are demonstrated in section **VIII** and some results of data processing are given in section **IX**. Lastly section **X** concludes the paper and outlooks into the near future.

II. CONFLATION

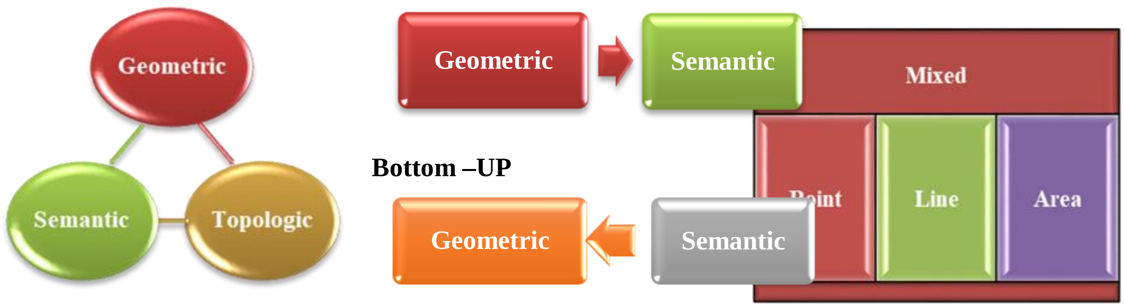
Conflation is known as the rehearsal of incorporating geographical datasets, joining multisource data, refining data excellence, and apprising spatial information. Not only vector datasets, but also raster datasets can be used for conflation. Merging vectorial data and raster data, indifferently being topographic maps or high-resolution imagery, is called hybrid conflation. Conflation is typically categorized into two sorts: horizontal and vertical [5]. Horizontal conflation refers to the unification of two end-to-end datasets with mutual edges, and the vertical conflation focuses on overlapping datasets covering the same area. The conflation history can be back-traced to 1985; Saalfeld [6] used the United States Geological Survey (USGS) and the Bureau of Census vector datasets to launch a project in the metropolitan areas of the U.S. After that, many applications were developed to realize automatic conflation. To manage the automated conflation, apart from distinct steps (e.g. pattern recognition, statistical analysis, graph theory), the basic procedures include positional alignment, matching feature identification, and positional and attribute matching feature the de-confliction process [7].

Since the beginning of the last decade and with the continuous developments in imaging and high-resolution remote sensing, automatic detection and extraction of objects from satellite imageries and airborne photos is one of the most vital encounters in the search responsibilities. Their basic complexity involved in the research questions is far from the most effective solution. Amid the huge number of workings, Fortier, Mena completed numerous assessments about road uncovering algorithms, Mayer and Rottensteiner studied this phenomenon as well[8][9].

Zhang and Mena deliberated matters tested by the GIS society: apprising GIS data requires wide-ranging physical work, whereas the low extraction proportion is the blockage of the image processing algorithm. Thus, a combined approach of existing geospatial databases and images seems to be a natural choice to increase the performance. Each dataset offers meaningful prior information for the other dataset [10, 11]. Zhang described a map-based road discovery technique, which comprised two significant applications: apprising the GIS data[9, 12, 13], and validating or increasing the road detection ratio[14, 15]. Mena reviewed the updating of GIS data and tried to classify the algorithms for road extraction and identified the challenges involved in the road detection using mutually vector and raster datasets.

III. FEATURE MATCHING

The definition of messaging objects from basic layers is a serious step in consolidation, as the same features can be represented heterogeneously in different data sets.The feature matching aims to search for similarities and establish relationships between similar entities.Wiemann and Bernard[3]classified the matching according to the method used to match the sequence and the geometry of input features (Figure 1.1). The processes can be categorized into bottom-up and top-down approaches, depending on either the sequence of node and edge matching or the sequence of semantic and geometric matching. Geometric matching dominates these matching methods (geometric, topologic and semantic criteria). It includes the similarity comparison of feature characteristics: length, area, perimeter, angle, Hausdorff distance, etc. Furthermore, the mixture of symmetrical, semantic and topologic alike is a drift in geo-data conflation. To identify the correspondence of source datasets, manual and automated matching is optional. Using manual matching is very laborious in areas with many elements [3].



Top-Down

a. Methods b. Sequence c. Input feature

Figure 1.1: *Classification of feature matching strategy.*

Point, line, area-based, and mixed are four input features of automated geometric matching [16]. The point-based approaches concentrate on the matching of adjacent points, which was first adapted in 1985 with a relatively long history compared with the other kinds of matching. Chen et al. [1] proposed an approach to integrate information utilizing control points extracted from common vector datasets and imagery. A specialized point pattern matching algorithm was developed with the concept of forming a transformation matrix. In the study implemented by Song et al.[17], they offered a relaxation-based point feature equivalent method to achieve the road juncture equivalent. This algorithm utilizes the relative distances between points and iteratively updates local context. Walter and Fritsch [18] successfully applied a “buffer growing” algorithm, the line-based method extends the traditional 1:1 matching to the 1:1, 1:n, and n:m pairs to be stored in a list.

Another clarification of line-based feature alike is the uncovering and toning of matching part nodes and poly-lines, as introduced by Filin and Doytsher[19]. Zone created conflation normally computes the belongings of polygons, for example, area, midpoint of magnitude, number of surrounded lines, percentage of intersection area-to-perimeter proportion, and the Hausdorff distance [20, 21]. The combination of point-, line-, and area-based matching is defined as a mixed model. A project carried out by Chen and Walter [18, 22] accomplish the matching between point and line features. The compound methods of identical point and zone features are used for the spatial conflation of non-planar polygons in aerial photos.

Between the exchange of datasets based on different conceptual models, semantic matching represents the similarity comparison of attributes. In the framework of semantic-alike attributes, a widespread facet to lessen semantic heterotypic differences is the ontology of GIS. Following the concept presented by Vaccari et al. [23]the ontology in the geospatial field is a logical theory indicating the objective of a formal vocabulary.

Li et al.[24]design a data meltdown and augmentation technique forimplementing multispectral WorldView-3 satellite images with selected GIS map datasets. They trained and evaluated four U-Net–based semantic segmentation models based on augmented and integrated dataset collections. Furthermore, they used the results obtained from the semantic segmentation frameworks and integrated a post-processing technique to further enhance the building extraction findings.

Wang et al. [25]propose a method to match road data with rural existing geospatial databasess, which is mainly focussing on spreading lines extensively. In this way, we can think of similarities between a potential identical couple in the general network structure rather than single line segments, ensuring a high match rate from other common methods. Meanwhile, the experimental result of 87.24% accuracy also proves the feasibility of this method.

Based on the subjectivity and regularity of the existing geospatial databases area, Zhu and Wang [13, 26]proposed a method to match the existing geospatial databases based on the improvement of particle swarm operations (PSO). Experiments have shown that due to its alignment with the algorithm, PSO greatly improves the efficiency of the algorithm, makes the algorithm more powerful, and improves the accuracy of compatibility with complex matching types to a certain extent.

Ronneberger et al. [27] are suggesting the application of a U-Net that connects feature maps from various stages to enhance layering accuracy. The U-Net mixes rear-stage detail information and front-stage semantic information, so accomplishing satisfactory performance on biomedical imageries layers.

Zhang et al.[28]proposed Residual U-Net(ResUnet)to bring out high-resolution remote sensing images. The suggested approach exceeds all the compared techniques; however, it demonstrates its high level over most techniques at that time. To this extent, a procedure is being created to go over junctions within the available units and among the codec trajectory of the network then eases dissemination of information, in both in and out computations.

Yuan et al.[5]used mobile phones as sensors as a promising and difficult way to collect traffic information for traffic management departments. In order to verify whether wireless positioning technology is feasible to collect traffic information, the process of map matching using GPS technology to provide moveableprobes in the suburban areas of Beijing is suggested. The map matching process includes two map matching algorithms, one is for each handover of map matching, and the other is for a handover sequence of map matching. The performance of the map matching process was verified by field data.

Map matching algorithms tend to make mistakes in intersection areas. The matching error at an intersection can seriously influence the system of navigation. Hui Qi et al. [29] present a decision domain model to be used to improve the HMM-based algorithm by a comprehensive study of the matching problem at intersections and related solutions.A ‘delayed’ matching is the core strategy of this algorithm.That is, the matching result output is as correct as possible (with the intersection as the result), when GPS points are in the error-prone area (inside the junction decision domain). However, the MHT-based algorithm strategy can also be applied, based on other matching algorithms, the evidence theory and interval analysis. It is important to note, that on-board GPS sensor data and a digital map are the only inputs for the algorithm proposed.

Raymond et al. [30]presented a simple HMM-based map matching method, whose performance was quite well on low-rate GPS trajectories. They tested the method on real-world data, and showed that it is comparable to the morecomplex method. It is interesting to see that the performance was still maintained even though the underlying existing geospatial databases was reduced by up to 46%. (The first work that tries to quantify the amount of road data that is sufficient for map matching using low-rate GPS trajectories). They found a way for theidentification of the best sampling rate of the existing geospatial databases for map matching,as the simplification can produce less accurate results.

Ma et al. [31]proposed an assessment technique for the GPS environment of urban road segments based on analysing massive and processing GPS trajectory historical data of busses. This method first took advantage of the unique feature that bus routes are fixed to construct the mapping from GPS data to road segments. The missing data were completed based on the inherent correlations among GPS errors and the environment information. They proposed a weighted strategy for the assessment of friendliness GPS environments, considering the impacts of GPS qualities on different devices.

Based on the existing map matching algorithm MMA theory, Liuet al. [32]did the following work: A priority-based MMA is designed. On the basis of demonstrating the factors that the angle between the speed direction angle and the road traffic direction is higher than the distance from the point to the candidate road segment, a method for calculating the angle between the speed direction and the road traffic direction is designed, also based on the regulations of the TransportMinistry. The GPS trajectory data and the verifying experimental results define the ratio of accuracy. Obviously, the accuracy of the algorithm in this paper exceeds 98.1%, which is better than any other similar algorithms.

Huh[33]propose a method for determining semantic matches between two data sets by finding hierarchical pairs of the corresponding m:n feature class. When nested analysis is applied to groups of objects within feature classes, the similarities between feature classes are estimated and displayed on a low-dimensional vector space, after applying the include graph method. Then, because classes of features with high similarity are distributed close to each other in the projection space, distance-based clustering is performed to identify linguistically the matching feature class pairs.

IV. FEATURE-BASED MATCHING ALGORITHMS

This section focusses on the matching algorithms for hybrid conflation of high resolutionimages and existing network data (vectorial spatial databases), with emphasis on feature-based approaches for points and lines. The semantic information included in the existing networks serves as information supplement to the features in the images.

Let us describe an overall matching algorithm as follows:

Let S be the reference point set {*s1, s2,⋯,sPs*}
($Ps \in \mathbb{R}$), and M is the target data set { $m_1, m_2, \cdots, m_{Pm}$ } ($P_m \in \mathbb{R}$), and $D(s_i, M)$ is the shortest distance from M to reference point s_i.

Then the algorithm starts as follows:

1) LetT_0be an initial parameter for the transformation;
2) Setup the correspondence function $C = \cup_{i=1}^{P_s} \{T_{k-1}(s_i), D(T_{k-1}(s_i), M)\}$;
3) Compute the new transformation k_T that minimizes the mean square error between point s in C.
4) Repeat steps 2~3 until having met the termination criteria.

a. POINT-BASED MATCHING

Point features in matching methods are often dealt with in a wide range of disciplines as they are relatively easy to discover from the image. However, there are many reasons why point-based matching is such a complex problem. Based on an analysis of progress on point-based matching with a specific focus on distortion level as well as the "dynamic" character of the data, Li et al. [34] claimed the underlying causes strongly influence both: accuracy and matching efficiency.The quality of the data and the level of distortion that can be subjected to data distortion are incompleteness and noise from different systems.Zitova and Flusser[35]reviewed the point-based matching approaches for the image registration . Zhang [36] proposed a point-based matching approach to support the network matching algorithm. Among these works, the ICP (Iterative Closest Point) algorithm (Besl and McKay[37]) has been reported as the most popular method for point-to-point matching. Kuppala et al. [38] reviewed image registration applications based on deep learning approaches having invariably convolution layers in the initial stages. Depending upon the applications, the network architecture for the subsequent layers differ across various registration applications. The ICP algorithm deals with an iterative procedure that computes the favourable correspondences with the initial matching by the assumption of knowing the prior information e.g. the similarity or transformation parameters.

b. ICP-REGISTRATIONALGORITHM

The ICP uses the closest neighborhood relationship to map the correspondence at each step. It requires a good initial estimate in order to approach the global minimum. ICP is simple and fast, and thus suitable for real-time applications. However, it is hard to express reasonable initial parameters. A fully automated ICP algorithm needs to search among several initial conditions that may increase computing efforts.

To find a desirable initial state of ICP, Chui[39]and Myronenko& Song[40]formulated in their methods of TPS-PRM (Thin Plate Spline Robust Point Matching) and Coherent Point Drift (CPD) the point matching as an optimization problem, which usually includes a target function. Unfortunately, the target function is an ill-posed problem, because of the large number of unknowns in the function and it needs regularized terms or constraints to get the optimal results. Moreover, the physical property of the spatial point is neglected. Apart from this drawback, these approaches are robust and general for different kinds of applications.

The point-based matching is a practical approach for point datasets, where the spatial relationship among the points is undefined or difficult to detect. The distance measure is a congenital deficiency of the point-based method. The nearest neighbor metric or its variation has been verified by Veltkampas[41]as a suitable measure for dense point datasets. The dense point dataset, however, is an unrealistic requirement for cartographic objects, which are usually irregularly and sporadically distributed within the study area. Another challenge for the method of point-based matching is caused by the outliers in the dataset and the noise may dramatically decrease the stability of the matching outcomes, if the signal-to-noise ratio becomes larger in the goal dataset.

The spatial relationships of the lines are conceptually classified into four groups, i.e. one-to-zero, one-to-one, one-to-many, and many-to-many [36]. The matching algorithms have the essential task to search the entire data space, and to detect the spatial relationships between homologous line features based on the established similarity measures.

Prokop et al. [42]introduce a novel method for point cloud data registration with small overlapping regions. They suggest a different approach rather than modifying existing methods on matching detected key points by the ICP algorithm. Although such methods have demonstrated to work well with almost totally overlapping scans, they are not effective in case of the problem of low overlapping regions. The key concept adopted by this work is to reduce the representation of scans by detecting line features in them and to perform a search to match the largest number of lines. In order to prune a large transformation parameter space, the parameters are found one by one with the resultant fitness being a combination of fitness functions of its individual parameters.

Lin et al. [43] introduces a three-dimensional alignment method based on matching two-dimensional local features. The suggested technique converts the point clouds to 2D bearing nook imageries and then uses the 2D images for a feature-based matching technique, called SURF, to locate matching pixel couples of two images. Those corresponding pixels can be used to get the original corresponding couple of the two 3D point clouds. Since the two corresponding point pair sets are usually more than three couples, only the top 50% of the best corresponding couples are used to find the optimal rigid body conversion matrix by a least squares estimation.

c. POINT REGISTRATIONS AND CONTROL POINT PROCESSING

Automatic registration is the method of transferring a point or point cloud into a defined reference system without employing manual measurements. Thus, some errors involved are eliminated without putting efforts on outlier detections manually. As described before, a well-known method for merging point data sets or point clouds is the Iterative Closest Point Algorithm (ICP), which supposes linear datum shifts. In order to derive exact geometric quality measures, we use the well-known Gauss-Helmert model for parameter estimation of the seven transformation parameters, which are unknown. In the following the math model used is described in more detail:

It is a well-known fact, that most implementations of ICP registration software do not consider at all any precision measures. If we consider the overall seven parameters transformation, which is non-linear, we get

$$X = Xo + \mu Rx \qquad (1)$$

with $\boldsymbol{X}$the $(3x1)_u$vector of world coordinates of$u$control points, $\boldsymbol{X_o}$the$(3x1)_u$vector of the 3 translation parameters(X_o, Y_o, Z_o), $\mu$is the scale, $\boldsymbol{R}$the $(3x3)_u$rotation matrix depending on the unknown rotation angles$\alpha, \beta, \gamma$and$\boldsymbol{x}$ the $(3x1)_u$vector of the local$u$control point coordinates. This non-linear transformation is linearized considering only differential changes in the three translations, the rotations and the scale, and therefore replacing (1) by

$$\mathbf{dx} = \mathbf{Sdt} \qquad (2)$$

$\boldsymbol{S}$is the$(3x7)_u$similarity matrix resulting from the linearization process of (1), given as

$$\boldsymbol{S}=\begin{bmatrix}1 & 0 & 0 & \vdots & 0 & -z & y & \vdots & x\\ 0 & 1 & 0 & \vdots & z & 0 & -x & \vdots & y\\ 0 & 0 & 1 & \vdots & -y & x & 0 & \vdots & z\end{bmatrix} \tag{3a}$$

and

$$\boldsymbol{dt'} = [dx_o, dy_o, dz_o, d\alpha, d\beta, d\gamma, d\mu] \tag{3b}$$

representing the seven unknown registration parameters. In order to estimate also the precision of the datum transformation, the ICP is therefore embedded in a least-squares solution for the Gauss-Helmert model for$u \geqslant 3$ and $\boldsymbol{B}:=\boldsymbol{S}$leading to

$$\boxed{1^{st}\text{ order: } \boldsymbol{Av} + \boldsymbol{Bx} + \boldsymbol{w} = \boldsymbol{0}, \quad \text{and} \quad 2^{nd}\text{ order: } D(\boldsymbol{v}) = D(\boldsymbol{l}) = \sigma^2\boldsymbol{P}^{-1}} \tag{4}$$

Solving$||\boldsymbol{v}||^2_{\boldsymbol{P}} = min$subjectto$\boldsymbol{Av}+\boldsymbol{Bx}+\boldsymbol{w}=\boldsymbol{0}$the corresponding normal equation system is obtained

$$\boxed{\begin{bmatrix}\mathbf{AP}^{-1}\mathbf{A}'\\ \mathbf{B}'\end{bmatrix}\hat{\boldsymbol{\lambda}} + \begin{bmatrix}\mathbf{B}\\ \mathbf{0}\end{bmatrix}\hat{\mathbf{x}} + \begin{bmatrix}\mathbf{w}\\ \mathbf{0}\end{bmatrix} = \mathbf{0}} \tag{5}$$

Resolving (5) wrt $\hat{\boldsymbol{\lambda}}$ we obtain

$$\hat{\boldsymbol{\lambda}} = -\left(\mathbf{AP}^{-1}\mathbf{A}'\right)^{-1}\left(\mathbf{B}\hat{\mathbf{x}} + \mathbf{w}\right) \tag{6}$$

and resubstituting again

$$-\mathbf{B}'\left(\mathbf{AP}^{-1}\mathbf{A}'\right)^{-1}\left(\mathbf{B}\hat{\mathbf{x}} + \mathbf{w}\right) = \mathbf{0}$$

$$-\mathbf{B}'\left(\mathbf{AP}^{-1}\mathbf{A}'\right)^{-1}\mathbf{B}\hat{\mathbf{x}} - \mathbf{B}'\left(\mathbf{AP}^{-1}\mathbf{A}'\right)^{-1}\mathbf{w} = \mathbf{0}$$

$$-\mathbf{B}'\left(\mathbf{AP}^{-1}\mathbf{A}'\right)^{-1}\mathbf{B}\hat{\mathbf{x}} = \mathbf{B}'\left(\mathbf{AP}^{-1}\mathbf{A}'\right)^{-1}\mathbf{w}$$

$$\boxed{\hat{\mathbf{x}} = -\left(\mathbf{B}'\tilde{\mathbf{P}}^{-1}\mathbf{B}\right)^{-1}\mathbf{B}'\tilde{\mathbf{P}}^{-1}\mathbf{w}} \qquad \text{mit } \tilde{\mathbf{P}} = \mathbf{AP}^{-1}\mathbf{A}' \tag{7}$$

The error propagation problem of any precision parameters is solved by the well-known law of error propagation (of statistical inference):

For the $(3x1)_u$vector of residuals we use

$$\hat{\mathbf{v}} = \mathbf{P}^{-1}\mathbf{A}'\hat{\boldsymbol{\lambda}} \quad \rightarrow \quad D(\hat{\mathbf{v}}) = \mathbf{P}^{-1}\mathbf{A}'D\left(\hat{\boldsymbol{\lambda}}\right)\mathbf{AP}^{-1} \tag{8}$$

and for the vector of the estimated unknown datum parameters

$$\hat{\mathbf{x}} = -\left(\mathbf{B}'\tilde{\mathbf{P}}^{-1}\mathbf{B}\right)^{-1}\mathbf{B}'\tilde{\mathbf{P}}^{-1}\mathbf{w} \rightarrow D(\hat{\mathbf{x}}) = \left(\mathbf{B}'\tilde{\mathbf{P}}^{-1}\mathbf{B}\right)^{-1}\mathbf{B}'\tilde{\mathbf{P}}^{-1}D(\mathbf{w})\tilde{\mathbf{P}}^{-1}\mathbf{B}\left(\mathbf{B}'\tilde{\mathbf{P}}^{-1}\mathbf{B}\right)^{-1} \tag{9}$$

With $D(\boldsymbol{w})=\sigma^2\boldsymbol{AP}^{-1}\boldsymbol{A}'$ substitutedin (9) the precision of the datum transformation parameters is propagated

$$\boxed{D(\hat{\mathbf{x}}) = \sigma^2\left[\mathbf{B}'\left(\mathbf{AP}^{-1}\mathbf{A}'\right)^{-1}\mathbf{B}\right]^{-1}} \tag{10}$$

This general derivation of a least-squares datum transformation using seven parameters can easily be reduced to 6 parameters (without scale), which is sometimes called Rigid Body transformation (RBT).

In the following, a Khartoum map matching experiment is accomplished. Here we use datum transformations to derive accuracy measures for the conflation of point data sets. For this reason, about 40 control points are measured using GNSS with an accuracy of about 1-2m. For the Khartoum OpenStreetMap (OSM) geospatial databases the following data accuracy has been obtained: σOSM (x,y)=2,2m. A similar accuracy has been found for the existing geospatial databases of the Sudanese Ministry of Infrastructure (SMI), which is σSMI (x,y)=2,7m. Although both datasets are not varying in precision very much, the completeness is quite different. In order to derive a value for completeness we compared the line segments of both datasets with each other.

Here a simple bit assignment helps the computer to differentiate for the available data:

line_segment = 1 (available)

line_segment = 0 (not available)

The following measures for completeness have been obtained, using the OSM road data network as reference (100%): Completeness (cps) of the SMI existing geospatial databases data to be 43%. Thus, there is a need for spatial conflation to update the official road database of Sudan.

The individual datasets of the existing geospatial databases are displayed in fig. 1.2 and 1.3 – fig 1.4 is an overlay of both.

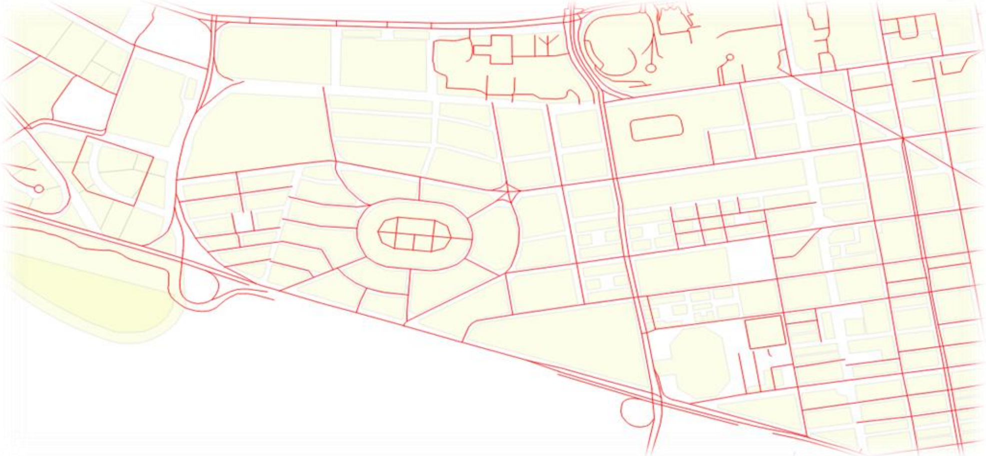


Figure 1.2: Open Street Map Khartoum state existing geospatial databases

Figure 1.3: Sudanese Ministry of Infrastructure (SMI) Khartoum state existing geospatial databases

In order to get the best results for an update of the Sudanese existing geospatial databases SMI we are looking for High Resolution Imagery of the WorldView-3 and -4 satellites to extract the center lines of roads automatically and to make a comparison in precision and completeness with OSM data. But this is future work do be done. Fig. 1.5 demonstrates this view by overlaying existing Google Maps images with the two vector layers of OSM and SMI geospatial databases.

Figure 1.4: Overlapping the data of OSM & SMI Khartoum state geospatial databases

Figure 1.5: Overlapping the data of OSM & SMI KRT geospatial databases with Google Satellite

d. LINE-BASED MATCHING

The line-based matching approach takes into account more engineering information than the point-based matching method and is widely used for existing geospatial databases matching. The geometric, topologic and semantic characteristics of two existing geospatial databases are useful clues for the establishment of an exact connection between them. The semantic information serves as auxiliary information while geometric and topologic information is more commonly explored[36]. The line-based matching algorithms work on existing geospatial databases with complete or incomplete topology.

The topology bears in mind the most significant information about a existing geospatial databases. A road segment is also an elementary component of the graph. Therefore, line-based matching is mostly supported by graph theory. Conte et al. [44]reviewed the interdisciplinary graph matching approaches with regard to the applications and the algorithms. They deemed the graph matching as a general searching problem with the aim to refine the correspondence among the line segments.

Different from the graph matching method, the existing geospatial databases matching plays a significant role for the integration of geospatial data and considers more information about the roads and their catchments' areas. Among the related works, two algorithms are quite compelling. Walter & Fritsch[18] proposed the buffer growing algorithm to identify correspondences inside a local region with a specific buffer threshold. Multiple correspondences are possible. However, the false correspondence can be minimized or verified as the buffer region moving to the neighbouring segments. Zhang[36] presented a line-based matching algorithm which helps to construct delimited strokes from the road segments, and then introduce a buffer around the individual strokes other than the fragmental road segments. In further steps, the multiple correspondences are identified and optimized by means of a context-related topologic analysis.

Wang et al.[25] introduce a functional representation for the Graph Matching (GM) problem. The main idea is to represent both the graphs and node-to-node correspondences by linear function spaces and linear functional representation maps. There are three main contributions that result from the functional representation. First, the representation provides geometric insights for the general GM, by which we can construct more appropriate objective functions and algorithms. Second, the linear representation map is a new parameterization approach for the Euclidean GM and helps to handle both conventional and geometrically deformed graphs. Third, the representation of graph attributes can be used as a replacement for the costly affinity matrix and reduce the space complexity. Finally, both efficient algorithms and an optimization strategy have been proposed to solve the proposed GM algorithms with better performance.

Wang et al.[45]propose an extending line-based matching scheme to calculate the road primitive similarity by taking into account the surrounding connections and contextual information.

e. PATCH-BASED MATCHING

The enclosed meshes or polygons by road segments also provide important clues for the matching algorithm, and we term the approach as patch-based matching. It follows the principle of finding the appropriate shape descriptor or indicator and computing the similarity between two patches. Since existing geospatial databasess contain open lines, patch-based matching can only partly work on closed meshes in existing geospatial databasess. Also, Zitova and Flusser[35]give a review with general discussion about the patch-based matching method.

Ma et al.[46]conduct extensive experiments to evaluate the performances of different representative methods to potentially provide an objective performance reference for researchers in the field of infrared and visible image fusion and consequently support relative engineering with credible and solid evidence. These approaches can be divided into seven categories: multi-scale decomposition-based, sparse representation-based, neural network-based, subspace-based, saliency-based, and hybrid methods and other models.

V. DECONFLICTION

With feature matching and feature alignment, non-collision is implemented later. By applying vertex insertion, weighted average, and feature connections, source data sets are combined [47]. In their work, the headers of the two sets of data are specified, so that the number and distances are equal. Then a weighted mean is calculated to characterize the accuracy of the data sets. Finally, crossheads are found according to tolerances. Creating a connection segment with a starting or ending point for an updated feature and unparalleled feature links, identical and unmatched features are found. Song et al. [48] first employed an approach and named it snakes. It improves the road accuracy from over 100 meters RMS to 3 meters. This model reduces the efforts to split linear features and transfer attributes of source datasets.

VI. STATE OF THE ART OF HYBRID CONFLATION

This section is devoted to an overview of the most important progresses of hybrid conflation between images and existing geospatial databasess. A complementary overview is given by Ruiz et al.[49]. Hild and Fritsch [50] introduced a global alignment method between vectors and images for geo-coding according to which the vector features are rasterized to match the extracted polygons from the image. Chen et al. [22]presented a conflation approach based on road intersection patterns recognized by using Bayesian classifiers. They analyzed the shape of the grayscale graph and identified clusters on the figure using a volume scale with the aim of detecting intersections of roads that reveal specific statistical properties. However, the majority of image areas do not really display statistical uniformity due to residual noise from small objects. To solve the problem, Ruiz et al. [49]developed a non-parametric approach based on texture analysis for the identification and extraction of pixels that belong to road intersections.

Chen et al.[51] develop a method to efficiently extract precise road areas from VHR remote sensing images to exploit spatial and spectral information. The method uses connected Gabor features as edge constraints for subsequent object division and region development processing. Edge restraints with proper completeness have proven valid in helping to separate road objects from numerous disturbances. This method can be attributed to reducing the lack of strict determination of thresholds in Gabor detection and zoning, non-automatic determination of the optimum scale range and unsatisfactory performance in delivering Gabor winding features.

Gao et al. [52]presents a semi-automatic approach that uses road seed points to extract road centrelines from VHR remote sensing images. An edge-constraint-based weighted fusion model was introduced to overcome the influence of road occlusion and noise on road extraction. Lastly, they proposed an edge-constraint fast matching method to get better quality and accuracy of the thoroughfare extraction results. The presented method is a superior and a practical solution for extracting methods from VHR optical remote sensing images.

Wu et al. [53] reported an approach to localize the global alignment problem by dividing a large image into regular grids, and then computing the maximum correspondence between the existing geospatial databasess and the features in each image grid. Finally, the matched features were transformed by the global TPS transformation function. The correspondence between the image and existing geospatial databases is identified by the peak responses from the corresponding gradient image. Moreover, it is assumed that there was a dominating orientation in each pre-tiled image. This assumption, however, proves too strict for the road pattern in the image, and is only suitable for certain cities. The approach also computing the confidence factor for the correspondence, and is thus providing useful information for manual corrections.

Song et al. [48]introduced a fully automated conflation technique based on the thoroughfare intersections as well as terminating which were extracted from images and likened with existing geospatial databasess by means of a relaxation labelling algorithm. The matched points were snapping using a Rubber-Sheet transformation algorithm. Furthermore, the aligned features were input into the snake models to acquire the refined results. In this approach, the intersections were picked up from the imagery by setting suitable thresholds for the Normalized Difference Vegetation Index (NDVI). The spatial context which assumed the road surface with a similar radiometric behaviour in the test area was considered. However, the image threshold was difficult to define: a small stroke might increase the resolution, but it missed some important crosshairs. However, a very loose threshold may increase the number of false intersections in the results.

These techniques have a common feature of avoiding detection of linear features and using intersections as the preferred salient features of the image. They have therefore a high computing complexity. Moreover, they ignore the shape of the road and presume the road segments are more or less straight lines, which may lead to inaccurate results after the transformation [54]. A combination of road intersection and salient road segments is therefore a more desirable approach, but it requires the extraction of linear features from the image.

Zhang[4]studied a Congruent Hybrid Model (CHM) in his dissertation and proposes a four step procedure:

1) A linear feature extraction approach consisting of a flexible circular mask (ECM) algorithm and a genetic algorithm (GA)-based clustering approach are applied to filter the extracted pathways;

2) A new approach to Sparse Matching Algorithm (SMA) is accomplished, which is particularly useful for dealing with the problem of multiple correspondences;

3) Evaluate the performance of two common transfer functions - the (RUBS) approach and the Thin Strip approach (TPS). He showed that the experiments with synthesized data as well as real spatial data have verified the time efficiency of the SMA, which has a stable performance. However, the required time of ECM and GA is relatively sensitive to the amount of the datasets. Compared to the classic point-based mixing model, the information exchange mechanism can achieve better results, especially with regard to engineering; Moreover, discrepancy in the two sets of data can also be recognized and corrected when the exact correspondence is derived from the SMA.

Xu et al.[55]accomplished experiments on a high-resolution remote sensing imagery dataset. The proposed model aimed to extract the local and global information of roads in the remote sensing imagery and improve the accuracy of existing geospatial databases extraction. The model clearly did well in tagging roads of different scales in remote sensing images due to the use of DenseNet blocks in various stages to guide feature recovery in the expansion portion.

Zhang et al.[56] proposed an automated building matching method based on relaxation labelling and pattern combinations. The method extended the object-level relaxation labelling matching method and constructed a probabilistic matching model considering both 1:1 object matching and 1:M pattern combination matching. The results of the experiments show, that the relaxation tagging process takes into account related information, reliably growing matching accuracy and is insensitive to non-rigid irregularities and homogeneity of shapes. Moreover, the pattern sets are newly integrated into the probability matching model, which efficiently improves the performance of matching crowdsourced construction data sets with large and uncertain differences in the spatial scale.

Lei and Lei [57]propose an alternative optimization model for the conflation problem, namely the network flow problem, which is computationally efficient and has more structural flexibility and a greater power for expressing the requirements of conflation. The proposed model focuses on solving the two- way 1:M matching problem. The model has a parameter p for the number of assignments, which is proportional to the maximum allowable match error.

Li and Cao [58]suggest a quick photo mosaic method used to extract the road surface from a single camera. The proposed method uses the key frames to remove excess information - a rough-to-accurate recording method is used to estimate model parameters, and a fast overlay method is used to merge the image. The method is simple and effective enough for practical applications, such as road surface diagnostics.

VII. SPATIAL CONFLATION COMPLEXITY

a. NON-RIGID DEFORMATION

The spatial datasets to be conflated or merged are usually calm from dissimilar times, different sensors and / or different owners, and there is necessarily some irregularity amongst them. The same object e.g. the road segment in one dataset appears different in other datasets and has undergone some non-rigid deformation. If we consider all the features at the same time, we have to face an infinite[59] number of unknown transformation parameters because the solutions usually exist in an infinite space [60] . To make the non-rigid transformation manageable, we may look for discrete solutions instead [61]. However, it is difficult to define the exact number for a sufficient estimation of the parameters, moreover, large transformation errors may be introduced if a feature to be matched is outside the convex hull of its matching partner.

Both continuous and discrete solutions can be reasonable for spatial conflation of existing geospatial databasess, but their relative efficiency and complexity need to be clarified in transformation applications. It should also be noted that distortions in data sets or imbalances between the two-existing geospatial databasess are not systematic and thus unrealistic to convert all features by one global function. Instead, each feature needs an individual treatment in an optimal way**.**

b. INCOMPLETE MATCHING MEASURES

The Iterative closest point (ICP) chooses the closest point as a matching scale, but it can be misleading for well-organized spatial features. The distribution patterns of spatial objects with natural or artificial structures are too diverse to be modelled in a single way. No versatile measures exist yet to effectively describe the similarity between the features and preserve their inherent characteristics. To choose or (re)define such measures remain the demanding task for a matching approach.

Both the correspondence and the transformation parameters are unknowns of the matching system, but they are interconnected with each other[39]. If we know the exact correspondence, the transformation is a simple least-squares problem, and vice versa. However, the high dimensional parameter space for both correspondence and transformation has complicated the handling of the non-rigid feature matching approach. In practice, it is only possible to get approximations by means of additional constraints or regularized parameters.

c. OUTLIERS (ROBUSTNESS, UNCERTAINTY)

One of the important preconditions of the matching approach is the equal or similar density of the datasets to be matched. However, it is not always the case for spatial data conflation, especially for the matching between existing geospatial databases data and satellite images. The road features in an image are often disturbed by noise such as shadow, tree etc., which make them difficult to recognize and only fragments of roads are discernible. The performance of the matching algorithm may drop further with the increasing noise or outliers in the dataset. This may lead to unstable and uncertain matching results. Under extreme conditions, for example, if the discrepancy between the two datasets is beyond a reasonable range, no reasonable solution can be achieved [53, 62].

VIII. DATASETS USED IN THE EXPERIMENT

a. OPENSTREETMAP

The OpenStreetMap (OSM) project is an online open source editable map of the world, created by volunteers worldwide through the collection and contribution of geographic data. Anyone can contribute to the map by simply registering on the OSM website. OSM is an open content licence with data, that is completely free-of-charge. Users can constantly update the data and may also add Areas-of-Interest. OSM has the potential to rely on volunteers from all over world including less developed regions, where obtaining data in such places can be difficult for most commercial mapping companies**.**

b. MINISTRY OF INFRASTRUCTURE IN KHARTOUM STATE

The Ministry of Infrastructure in Khartoum state is responsible of public infrastructures, such as transport infrastructure, road planning, urban development and other civil services. It plays an important role in creating maps that can be used by different governmental sectors in Khartoum state.

IX. EXPERIMENTALDATA

The table below show the waypoints of the area under study and their attributes:

POINT (P)	LOCATION		ELEVATION (Feet)	Precision (M)
	S (Deg)	N (Deg)		
P1	15.60258	32.51099	1275	2.61
P2	15.59981	32.50915	1279	2.83
P3	15.60035	32.50558	1277	2.91
P4	15.60337	32.506360	1271	2.70

X. CONCLUSIONS AND OUTLOOK

In this paper we gave an overview on the state-of-the-art of hybrid conflation, as a tool to update existing geospatial databases. This is a very urgent problem, especially for developing countries like Sudan. It might be the most efficient method to use crowd-sourced data and images form airborne and space-borne platforms.

The following points are summarizing the problems encountered during the experiment from the Khartoum datasets:

- OpenStreetMap dataset

As mentioned in the previous section, OpenStreetMap can be modified by volunteers around the world, and this may lead to misleading information by adding or removing content such as roads, unlabelled buildings, and many other useful information. Tools used by OpenStreetMap can also lead to steering problems such as disconnected roads and inappropriate cornering restrictions.

- Ministry of Infrastructure dataset

The maps produced by this organization lacks of accurate and up-to-datee information and positioning as it appears in (Figure 1.4); it is obvious that there is an overlap of data between this dataset and the OpenStreetMap.

The comparison made in the experiment did produce first results. We have exposed, that the existing geospatial databases dataset of Sudanese Ministry of Infrastructure was suffering for completeness - thus any mean to get better results is welcomed. As such, the ICP algorithm we used to be finally a least squares estimation in the Gauss-Helmert model of statistical inference, well-known in geodesy. The great advantage of this model is its ability to estimate not only the unknown parameters of a spatial similarity transform but to deliver also the precision measures. In this way classical ICP is extended by necessary information being used in an overall statistical analysis of accuracies and completeness. One drawback of this method so far is the restriction to process point data sets or point clouds only.

The outlook for our future work is as follows. We would like to extend the point-wise Gauss-Helmert model to process also lines and areas, to have a more general toolkit for spatial conflation. This would include the direction of lines as additional parameters to be estimated. Furthermore, we would like to make experiments with high resolution optical satellite images. WorldView-3 and WV-4 high resolution satellite imagery are delivering ground sampling distances (GSD) of about 0,3m and thus are excellent geospatial resources to apply hybrid conflation algorithms and making further completeness and accuracy studies.

The high-resolution satellite imagery will be used as reference to compare it with OpenStreetMap data to reach the research objectives. Here we assume that the satellite imagery is correctly registered in a global coordinate system. In case the points and line segments in both systems are matching each other very well, then a perfect coincidence would have been met. In case a match is not found then a displacement should be made in the OpenStreetMap points and lines to the nearest points and lines of the satellite imagery. Here we will convert the street segments into both systems and will then use an extended ICP algorithm embedded in the Gauss-Helmert model to solve the mission problem.

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