MULTILEVEL ANALYTICAL AND VISUAL DECISION FRMEWORK FOR IMAGERY REGISTRATION AND CONFLATION

George G. He, Senior Spectral Scientist
EOIR Technologies, Inc.
703.490.5292x28
703.490.5293(fax)
ghe@eoir.com

Boris Kovalerchuk, Professor
Central Washington University
703.490.5292x15
703.490.5293(fax)
Boris.Kovalerchuk@cwu.edu

Thomas H. Mroz, Project Manager
National Energy and Technology Laboratory
Department of Energy
Morgantown, WV, 26056
Thomas.Mroz@netl.doe.gov

ABSTRACT

National security analysis, as well as analysis of matters of economic and scientific interest, benefits from the utilization of multiple geospatial information sources. These information sources are increasingly becoming higher in dimension and precision. Imagery and its extracted information become increasingly more complex to integrate under time and space operational constraints. The process, extraction, and use of geospatial information are becoming more and more automated. The trend towards automation demands better data quality and confidence measures. In the case of conflation, disparate data sources carry inaccuracies and render the standard error analysis, the dependent-and-independent variable analysis methodology, less useful. This paper establishes a conflation and registration structure using an Analytical and Visual Decision Framework (AVDF). This framework recognizes that pure analytical methods are not sufficient for solving spatial analysis problems such as integrating images and their derived vector products. The AVDF consists of a complexity space, conflation levels, and a disparity structure for the mapping of two input data sources. The AVDF transforms the mapping from an opportunistic to a more definitive mathematical approach. A partial differential equation (PDE) approach is used to initiate the understanding of the modeling of disparities between data sources for a given mapping function. The PDE approach is the integral part of the framework that systematically addresses the complexities in the integration of information through conflation framework, methods, computational functions and algorithms

INTRODUCTION

For computational based information integration, the term **registration** is defined as the finding of one and only one *mapping function* between two geospatial information sources, while **conflation** resolution is defined as the matching of geospatial information sources, with both matched and un-matched features identified; i.e., spatial and feature matching are location and attribute dependent. The purpose of conflation is to combine information from data sources for the potential of creating a new dataset that is better than the originals; i.e. information gain. The conflation framework builds on the fundamental components that an expert would resolve in a specific conflation task. In general, the conflation of imagery and its derived products would have three controlling factors: accuracy specification, algorithm complexity and computation requirements.

Mathematically fundamental to conflation is the mapping between two different information sources. Geometric disparities or inconsistencies (i.e., misalignment) may be global, local or subpixel in scope. Global disparity, image wide, is analogous to similarity and direct linear transformation models in the domain of photogrammetry. Local disparity, on the order of 100s of pixels, parallels the use of Affine and Rational Polynomial Coefficient transformations for registration. While all these models have analytical solutions, the modeling of subpixel disparities remains an elusive research objective. The focus for this paper is the process and mathematics that model the disparities at global, local. A proper model at local level is predicted to be beneficial to subpixel level information integration.

Disparity analysis using partial derivatives is essential to evaluate the quality of information integration. For conflation, a mapping function, continuous or discrete, between the input data sources, is necessary and required, but often incomplete. The function used first to initiate the mapping in the conflation process is generally an approximation. A selected function for the initial mapping is often the simplistic similarity model. The rotation, scaling and translation parameter between two image sources are either simultaneously or iteratively resolved. It is a known fact to the remote sensing community that the quality of the mapping decreases from the center to the edges and corners of the imagery. The PDE approach is used as an attempt to understand the contributions from each of the modeling parameters, and to provide a metric to further improve the models.

ANALYTICAL AND VISUAL DECISION MAKING (AVDM)

AVDM refers to a process using visual environments by and/or for decision makers to acquire quality information to support spatial decision making. Decision making is a nonlinear process either purely visual or combined with analytic means. Conflation results from decision making with multiple information sources can be either visual and/or analytic. An example of visual conflation includes the utilization of information sources presented on maps. A typical analytic conflation resolution involves the use of computer to solve analytic functions that map among images and their products. The purpose of integrating visual and analytic means for registration and conflation is to combine information efficiently from data sources for the potential of creating a new dataset that has better geospatial consistency than the originals. To achieve better-fused data quality, different algorithms and methods are permissible under AVDF and its different stages of data and information processing. The fact that no one has yet achieved fully automated conflation, and that very few researchers are working on imagery to vector registration, point to the reality of the challenges in the conflation process.

The AVDM provides a multi-level and/or multi-stage solution for registration and conflation using multiple observations with requirements across multiple scales of geographical extents and attributes. AVDM has three integral parts; i.e., complexity space, conflation levels, and disparity structure analysis. The complexity space provides a framework to view, identify, establish, and partition the conflation objectives. The conflation levels are to provide a process and mechanism to navigate through the compartmentalized complexity subspace if and when a conflation objective is partitioned into actionable conflation levels. Disparity analysis, the focus of this paper, provides a mathematical framework and quantities for constructing a practical process and its associated algorithms to estimate and/or solve the conflation problem at a specific level.

DISPARITY STRUCTURE ANALYSIS IN AVDM

The objective of disparity structure analysis for conflation is a mathematical framework to partition the residuals and relate them back to the original input measurements, and the measurement unit. Disparity structure is referring to the inconsistency between the data sources, in contrast to the error defined for the difference between a measurement and the truth. In the case of error analysis, there are two sets of input variables, dependent variables containing measurement error, and independent variables containing no measurement error. The model in the error analysis scenario that maps the two sets of variables is definitive. Conflation deals with sets of measurements that all contain errors, with the sources of errors not well understood. There may not exist an exact function to map one set of measurements to another. The function used to initiate the conflation process is necessarily an approximation. Thus, an understanding of disparity structure for a given selected function becomes an important factor in conflation decision-making. Partial derivative, rather than least square, approach is used o account for the fact that all measurements contain error. The similarity transformation is proposed as an initial approximation to reveal the disparity structure in the geospatial conflation scenarios. The structure derived from the partial derivative approach, based on the similarity transformation, facilitates the comprehension of the modeling of disparity components in terms of rotation, translation, and scaling in the framework of the physical model approach.

The compact form of a typical photogrammetric similarity transformation is described in equation (1). Equation (1) has three components: translation, rotation, and a *single* scaling factor.

$$\begin{bmatrix} X_T \\ Y_T \end{bmatrix} = \begin{bmatrix} X_s \\ Y_s \end{bmatrix} - S \begin{bmatrix} Cos\theta & -Sin\theta \\ Sin\theta & Cos\theta \end{bmatrix} \begin{bmatrix} X_c \\ Y_c \end{bmatrix} \qquad (1)$$

where: X_T , Y_T are the translations along the X and Y axes,
X_s , Y_s are the coordinates from the standard,
X_c , Y_c are the coordinates from the conflation source,
S is the single scaling factor,
θ is the rotation angle between the two sources.

Using the sum of squares of the disparity to describe the total conflict information, equation (1) is expanded into equation (2). The partial derivative approach results in 30 different terms as shown in the right side of Equation (2).

$$\begin{aligned}
&d^2X_T + d^2Y_T = dX_s^2 + S^2Cos^2\theta d^2X_c + S^2Sin^2\theta d^2Y_c + \\
&S^2(Sin^2\theta X_c^2 + Cos^2\theta Y_c^2)d^2\theta - 2Cos\theta SdX_c dX_s \\
&+2Sin\theta SdY_c dX_s + 2Sin\theta SX_c d\theta dX_s + 2Cos\theta SY_c d\theta dX_s \qquad (2) \\
&-2Cos\theta Sin\theta S^2 dY_c dX_c - 2Cos\theta Sin\theta S^2 X_c d\theta dX_c \\
&-2Cos^2\theta S^2 Y_c d\theta dX_c + 2Sin^2\theta S^2 X_c d\theta dY_c \\
&+2Cos\theta Sin\theta S^2 Y_c d\theta dY_c + 2Cos\theta Sin\theta S^2 Y_c X_c d^2\theta \\
&+dY_s^2 + S^2Sin^2\theta d^2X_c + S^2Cos^2\theta d^2Y_c + \\
&S^2(Cos^2\theta X_c^2 + Sin^2\theta Y_c^2)d^2\theta - 2Sin\theta SdX_c dY_s \\
&-2Cos\theta SdY_c dY_s - 2Cos\theta SX_c d\theta dY_s + 2Sin\theta SY_c d\theta dY_s \\
&+2Cos\theta Sin\theta S^2 dY_c dX_c + 2Cos\theta Sin\theta S^2 X_c d\theta dX_c \\
&-2Sin^2\theta S^2 Y_c d\theta dX_c + 2Cos^2\theta S^2 X_c d\theta dY_c \\
&-2Cos\theta Sin\theta S^2 Y_c d\theta dY_c - 2Cos\theta Sin\theta S^2 Y_c X_c d^2\theta
\end{aligned}$$

After simplifying the 30 terms, equation (3) results. Equation (3) presents a choice of grouping the disparity types using terms from sources designated as the standard or conflict. The cross terms contain contributions from both the standard and conflicting sources.

$$d^2X_T + d^2Y_T \Rightarrow Total\ \ disparity$$

Disparity due to Standard source

$$= dX_s^2 + dY_s^2 \Rightarrow Trans.\ \ disparity$$

Disparity due to Coflicting source

$$+S^2d^2X_c + S^2d^2Y_c \Rightarrow Trans.\ \ disparity$$

$$+S^2(X_c^2 + Y_c^2)d^2\theta \Rightarrow Rotation\ \ disparity$$

$$+2S^2d\theta(X_c dY_c - Y_c dX_c) \Rightarrow Cross\ \ terms\ \ (rotation \,\&\, trans.)$$

Disparity due to cross terms of Standard and Coflicting sources (3)

$$\begin{aligned}+2S*(&Sin\theta dY_c dX_s - Cos\theta dY_c dY_s\\ &- Sin\theta dX_c dY_s - Cos\theta dX_c dX_s\\ &+ Sin\theta X_c d\theta dX_s - Cos\theta X_c d\theta dY_s\\ &+ Sin\theta Y_c d\theta dY_s + Cos\theta Y_c d\theta dX_s)\end{aligned}$$

Equation (3) shows that conflict has 3 top levels of structures, assuming a constant scaling:

1) terms for conflict due to error from the designated standard source;
2) terms for conflict due to the designated conflict source; and
3) terms for conflict that intersects the designated standard and conflict sources.

According to Equation 3, the disparity due to transition error from the designated standard source is not location dependent. The location dependent conflict terms consist of multiplicative factors; e.g., coordinates, angle, in addition to the derivative. For the given similarity model, the dependencies are linear for these terms that are related only to the designated conflict sources. The terms that describe the conflict between the designated standard and conflict sources have location dependent and independent components, all of which are nonlinear.

In essence, the integration of data has some prospect of providing better information. However, conflation resolution also presents opportunities to introduce new disparate sources for conflation resolution. The new source of disparity can be potentially larger if the mapping function or its parameter derivation is deemed incompatible with the data sources, or the disparity contributing factors are inappropriately modeled. This makes the PDE and the disparity structure analysis important components of AVDF, because among the conflict terms, the assessment of disparity terms that are *location dependent* can provide key information for improving the conflation resolution.

The coupling and magnification of location dependent and angle-measurement error terms arguably will be the most challenging disparity to quantify, particularly when the location independent terms are not well modeled, with the disparities transferred to the rotation terms. This necessitates a *visual decision making* framework to compliment the analytic analysis methodologies and algorithms. For example, if the translation error terms from the designated standard information source are ignored (as in the standard dependent-and-independent variable analysis method), the corresponding disparities have to be compensated by the other terms in the equation. The disparity transition will create additional inconsistencies in the subsequent analysis.

To test the location and angle dependency, a feature model was built to determine how patterns of change are revealed and how resolutions can be applied. The base model consisted of a grid of discrete points on a Cartesian plane in the shape of an ellipse to be used as an extracted image feature (figure A). From this base, two image models were constructed. While maintaining indices on these points in an image model, the X,Y values are modeled through axis translations, rotation around the origin, scaling, or a combination of these items in different orders of operation, including the addition of Gaussian noise.

These two image models were compared, and the ΔX , ΔY , θ (direction of change with respect to the source image), and the distance (magnitude) between the indices were extracted. To evaluate the results, these values were projected into a mesh in a 3 dimensional Cartesian system using the X,Y values of the source image indices and the comparative values in the Z axis. (Figure B.) The results revealed that there were consistent patterns of disparity. Rotations and magnifications of image features resulted in a cone shaped pattern in the magnitude values from a center point (Figure B). Further modeling is currently underway to study the location dependency and nonlinearity. This is the beginning of applying the disparity structures and models to understand the conflation phenomenology.

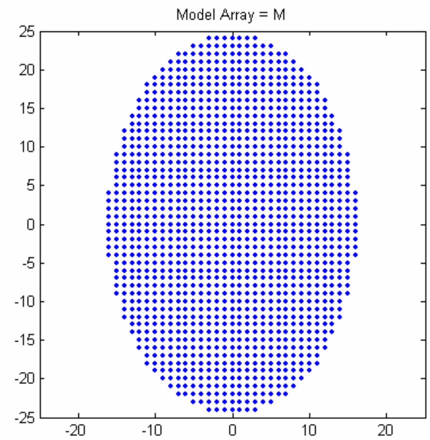

Figure A. theoretical model ellipse

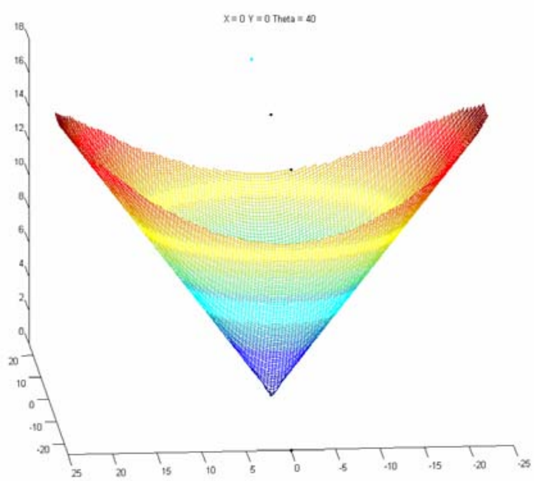

Figure B. surface mesh of magnitude changes in the model indices as a result of figure rotation and comparison between the input models

CONCLUSION

Scientific, economic, and national security interests gain benefits from decisions made utilizing multiple information sources. This research investigates a systematic approach to address the spatial disparity complexities in the integration of information derived from imagery. The disparity structure and analysis is fundamental to the three important aspects in addressing the information integration; i.e., decision making framework, levels of conflations, and information quality.

The similarity transformation is arguably the simpler photogrammetric model closer to the physical model than the general affine or rational polynomial coefficients transformations. The PDE method is generally applicable to any of the models for describing the disparities with different sets of parameters. The selection of different models is largely mission specific and data dependent. The PDE approach provides the ability to separate disparities into location dependent and independent terms; and the location dependent disparity may further be subdivided into linear and nonlinear terms. When the disparities show large dependency on location, it is necessary for the mapping function to be refined to accommodate the spatial variation through space partition, more terms of the linear equation, and/or higher order equations.

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