Effective Association of SAR and AIS Data Using Non-Rigid Point Pattern Matching

To cite this article: Z Zhao et al 2014 IOP Conf. Ser.: Earth Environ. Sci. 17 012258

View the article online for updates and enhancements.

Related content
- Review of Road Extraction Methods from SAR Image
  N Sun, J X Zhang, G M Huang et al.
- Satellite observations of oil spills in Bohai Sea
  Y L Wei, Z Y Tang and X F Li
- SAR image segmentation based on the advanced level set
  S Y Luo, L Tong, Y Chen et al.
Effective Association of SAR and AIS Data Using Non-Rigid Point Pattern Matching

Z Zhao, K.F Ji, X.W Xing, H.X Zou
School of Electronic Science and Engineering, National University of Defence Technology, Changsha, Hunan, P. R. China, 410073.

Email: zhaozhi_nudt@yahoo.com

Abstract Ship surveillance using multiple remote sensing sensors becomes more and more vital presently. Among the various sensors, space-borne Synthetic Aperture Radar (SAR) is optimal for its high resolution over wide swaths and all-weather working capabilities. Meanwhile, Automatic Identification System (AIS) is efficient to provide ship navigational information. Limited to the progress of ship surveillance using SAR image only, the integration of them significantly benefits more. Data association is the fundamental issue. Many algorithms have been developed including the Nearest-Neighbour (NN) algorithm, the Joint Probabilistic Data Association (JPDA) method, and the Multiple Hypothesis Testing (MHT) approach. Ship positions derived from SAR image can be associated with the ones provided by AIS. State-of-the-art method (NN algorithm) is proved to be feasible. But it faces more challenges under adverse circumstances, such as high-density-shipping condition. We investigate the non-rigid Point Pattern Matching (PPM) method to solve this problem. To the best of our knowledge, this paper is the first to introduce non-rigid PPM to the data association of SAR and AIS. On the basis of introduction to the data association, Coherent Point Drift (CPD) algorithm is investigated. Experiments are carried out and the results illustrate that the CPD algorithm achieves higher accuracy and outperforms state-of-the-art method, especially under high-density-shipping condition.

Keywords Ship surveillance, Non-rigid, Point Pattern Matching, Coherent Point Drift

1. Introduction
Ship surveillance plays an important role in maritime safety and security. It has been widely used in environmental monitoring, track and rescue, anti-piracy and military reconnaissance, etc. With the rapid development of space-borne SAR and AIS, ship surveillance characterized by near real time and global coverage has come true. Space-borne SAR has advantages of high resolution over wide swaths and all weather working capabilities, but ship detection and identification using SAR image are very limited especially under the high-sea-state condition. Space-based AIS is superior to terrestrial AIS in the surveillance of open sea area, which could only cover up to 40 km off the coast. AIS messages always have errors, and not all the ships equip or operate with it. On consideration of cooperative nature space-borne of SAR and AIS for ship surveillance, the integration of them would benefit it significantly. Ship surveillance by the integration of space-borne SAR and AIS has attracted much attention [1,2]. It is mainly the issue on information fusion. The fundamental problem is data association, which relies on the characters of SAR image and AIS data.
State-of-the-art association method is based on position information [3-6]. The flowchart of space-borne SAR and AIS data association is shown in Figure 1. It illustrates that the data association merely consists of Time Matching step and Position Matching step. In the time matching step, firstly filtering is implemented according to the imaging space-time information. And then, the filtered AIS data need to be validated to secure the accuracy using prior knowledge or database. If the AIS data is valid, position projection is carried out to get the estimated ship position at the image acquisition time. In the position matching step, position prediction is accomplished to get AIS-predicted position by compensating the Doppler shift. The centroid positions derived from space-borne SAR image are not the true positions. There exist only azimuthal displacements with AIS-report positions theoretically. But the system errors (such as SAR image geo-location accuracy and GPS positioning) always lead to differences between the AIS-predicted position and the corresponding SAR contacts, so searching and matching is necessary to find out the accurate association results.

Nearest-Neighbor (NN) algorithm is widely used in Searching/Matching. It simply sets the nearest one as the output, and probably not efficient for the high-density-shipping condition. Additionally, the prediction for ship movement is more difficult when the ship has stronger yaw, roll and pitch motions itself. So the position projection step may bring more errors, which result in difficulties in searching and matching. To solve the problems illustrated above, an improved method is proposed in this paper. In the second section, the detailed matching method based on Coherent Point Drift (CPD) is investigated. Simulations are presented in section three. Section four refers to conclusion.

2. Methodology
This section mainly investigates the application of CPD in the step of position searching and matching for space-borne SAR and AIS data association, and presents the detailed approaches.

2.1. Feasibility Analysis
Point set registration is to assign correspondences between two point sets and/or to recover the transformation that maps one point set to the other [7]. In this issue, the centroids of targets detected in the SAR image make up one point set. AIS-predicted ship positions gained after projecting and azimuthal shifting operations constitute the other point set. The two point sets have differences only in azimuthal displacements theoretically without considering other errors. Even though the system errors are not neglected, they also keep similar topological structure approximately (see Figure 2&3).

The two point sets do not satisfy simple transformation. Irregular distortions always exist. Non-rigid PPM method adopts non-linear geometrical transformation models to solve the irregular distortion problems. So it is better than rigid Point Pattern Matching (PPM) method to deal with this issue. CPD algorithm can either be used in rigid or non-rigid case. It has better flexibility for point sets registration.

Figure 1. Space-borne SAR and AIS Data Association Flowchart.
2.2. The Coherent Point Drift Algorithm

The Coherent Point Drift algorithm [7] for non-rigid point pattern matching is essentially a maximum likelihood (ML) estimation problem. The alignment of two point sets can be considered as a probability density estimation problem. The Gaussian mixture model (GMM) centroids (representing the first point set) are fitted to the data (the second point set) by maximizing the likelihood. They are forced to move coherently as a group to preserve the topological structure of the point sets.

Here supposes that the first point set is made up of AIS-predicted positions, and the second one is composed of ship centroids derived from SAR image. Firstly, the notations are given below. Dimension of the point sets is denoted as \( L \). The number of points in the two point sets is \( A \) and \( B \) respectively. \( \Phi_{A:L} = (\phi_1, \phi_2, ..., \phi_A)^T \) denotes the first point set, and \( \Psi_{B:L} = (\varphi_1, \varphi_2, ..., \varphi_B)^T \) the other. \( d(Z) \) denotes diagonal matrix formed from vector \( Z \). \( T(\Phi, \zeta) \) denotes the transformation applied to \( \Phi \), and \( \zeta \) is a set of transformation parameters. \( I \) and \( 1 \) denote the identity matrix and the all-ones-column vector respectively.

The transformation is defined as the initial position plus a displacement function \( \Gamma \):

\[
T(\Phi, \Gamma) = \Phi + \Gamma(\Phi)
\]

To enforce the smoothness of this function, the norm of \( \Gamma \) is necessary. In the Hilbert space \( H^m \), a norm of \( \Gamma \) is defined as:

\[
\|\Gamma\|_m = \int \sum_{k=0}^{m} \left\| \frac{\partial^k \Gamma}{\partial \xi^k} \right\|
\]

(2)

The norm in the Reproducing Kernel Hilbert Space could be defined as:

\[
\|\Gamma\|_r = \int \frac{\Gamma(f)^2}{G(f)} df
\]

(3)

where \( G \) is a unique kernel function associated with the Reproducing Kernel Hilbert Space, and \( G \) is its Fourier transform. \( \Gamma \) is the Fourier transform of the function \( \Gamma \). \( f \) is a frequency domain variable. The Fourier domain norm defined above has been used to regularize the smoothness of a function.

Then the regularization term can be expressed as:

\[
\xi(\Gamma) = \int_0^\infty \frac{\Gamma(f)^2}{G(f)} df
\]

(4)

where \( G \) is a Gaussian, but not related to the Gaussian form of the distribution chosen for the mixture model. The Gaussian is chosen to make the regularization term equivalent to the one in the Motion Coherence Theory:

\[
\xi_{MCT}(\Gamma) = \int_0^\infty \sum_{i=0}^{m} \frac{\beta_{2i}}{s2^i} \|D^{2i}\Gamma(x)\|^2 dx
\]

(5)

where \( D \) is a derivative operator. \( D^2 \Gamma = \nabla^2 \Gamma, D^{2+s} \Gamma = \nabla(\nabla^2 \Gamma) \), where \( \nabla \) is the gradient operator.
and $\nabla^2$ is the Laplacian operator. Parameter $\beta$ reflects the amount of smoothness regularization and defines the width of smoothing Gaussian filter.

The regularization term in (4) with a Gaussian choice of low-pass filter $G$ is equivalent to the regularization term in (5). This implies that motion coherence is imposed among the points.

The CPD non-rigid point set registration algorithm can be summarized as below according to [7]:

- Initialization. The matrix of coefficients $W = 0$, the equal isotropic covariance:

$$\sigma^2 = \frac{1}{\text{LAB}} \sum_{k=1}^{4} ||\phi_k - \phi_0||^2$$

Initialize parameter $\omega$ ($0 \leq \omega \leq 1$), which reflects the amount of noise in the point sets. $eta > 0$.

Parameter $\lambda$ ($\lambda > 0$), which represents the trade-off between the goodness of maximum likelihood fit and regularization.

- To construct the kernel matrix $G$:

$$g_{ij} = \exp \left( -\frac{||\phi_i - \phi_j||^2}{2\sigma^2} \right)$$

(7)

- To implement EM optimization including E-step and M-step, repeat until convergence.

E-step: to compute matrix $P$:

$$p_{ab} = \frac{\exp \left( -\frac{||\phi_a - \phi_b||^2}{2\sigma^2} \right)}{\sum_{b=1}^{B} \exp \left( -\frac{||\phi_a - \phi_b||^2}{2\sigma^2} \right) + \frac{\omega}{1-\omega} \frac{(2\pi\sigma^2)^{1/2}B}{A}}$$

M-step: to solve the equation:

$$(G + \lambda \sigma^2 d(P1)^{-1})W = d(P1)^{-1}\Phi - \Psi$$

(9)

where $d(\cdot)^{-1}$ the inverse diagonal matrix. Set $A_p = \text{tr}(\Phi^T d(P1) \Phi)$, $T = \Psi + GW$, then

$$\sigma^2 = \frac{1}{A_p} \left( \text{tr}(\Phi^T d(P1)^{-1} \Phi) - 2\text{tr}((P \Phi)^T T) + \text{tr}(T^T d(P1) T) \right)$$

(10)

- The aligned point set is:

$$T = T(\Psi, T) = \Psi + GW$$

(11)

And the probability of correspondence is given by $P$.

3. Simulation Results

Traditionally, there exist more ships near the coast or port, and fewer ships in the open sea area, so the dense and sparse conditions should be considered. Meanwhile, the ships detected in the SAR image may not have the corresponding AIS reports. The quantities of points for the two sets are not to be always equal, and outliers always exist. The systematic errors are also unavoidable especially when the ship’s movement is non-linear and the sea state is coarse. Additionally, the estimation accuracy for Doppler displacements affects the topological deformations between the two point sets.

Considering the typical conditions mentioned above, this section presents the simulation results of four conditions.

- **Condition I**: Not high-density-shipping condition (see Figure 4), considering the stochastic errors. The registration results using CPD and NN are shown in Figure 6, which both performed accurately.

- **Condition II**: High-density-shipping condition (see Figure 5), considering the stochastic errors’ influences on the azimuthal displacements, which are all positive and underestimated, or negative and overestimated. Figure 7 shows the results of CPD based method with no errors, and the results of NN based method with error in the black solid ellipse.

- **Condition III**: Similar to condition II, but the azimuthal displacements are underestimated partially and overestimated partially (see Figure 8). The similar results are shown in Figure 10.

- **Condition IV**: High-density-shipping condition (see Figure 9), there exist three outliers representing three ships detected in the SAR image but with no corresponding AIS reports
(circled by black ellipse). Figure 11 shows the matching results. CPD-based method performs better than the NN-based method. In the black rectangle, the outlier is wrongly associated with one AIS report, which actually corresponds with another SAR contact. On the contrary, if there are some ships not detected in the SAR image but reported by AIS, the outliers would appear in the point set of AIS-predicted positions and the matching results are similar.

Figure 4. Point sets derived for condition I.

Figure 5. Point sets derived for condition II.

Figure 6. The comparison for condition I based on CPD and NN.

Figure 7. The comparison for condition II based on CPD and NN.

Figure 8. Point sets derived for condition III.

Figure 9. Point sets derived for condition IV.

Figure 10. The comparison for condition III based on CPD and NN.
4. Conclusion
This paper investigates an improved data association method of space-borne SAR and AIS based on non-rigid point pattern matching. CPD, a non-rigid point registration method, is introduced to the data association of space-borne SAR and AIS for the first time. It uses the similarity of topological structures and has higher flexibility. The simulations are carried out for typical conditions, which emphasize the high-density-shipping conditions, and also the conditions that there exist outliers (e.g., SAR contacts with no corresponding AIS reports, etc.). The association results validate that the CPD-based method achieves better performance than the NN algorithm, especially under the high-density-shipping condition.

Furthermore, SAR and AIS data association based on multiple feature information fusion could also be considered. Not only the position feature is considered, other features such as size, speed and course can also be jointly used to improve the accuracy of data association in the future.

References
[1] Brusch S, Lehner S, Fritz T, Soccorsi M, Soloviev A and Schie B. 2011. Ship Surveillance With TerraSAR-X. IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING. 49 pp 1092-1101.
[2] Yang C and Kim T. 2012. Integration of SAR and AIS for ship detection and identification. Ocean Sensing and Monitoring. Proceedings of the SPIE. 8372 pp.1-6.
[3] Vachon P W, English R A and Wolfe J. 2007. Ship Signatures in RADARSAT-1 ScanSAR Narrow B Imagery Analysis with AISLive Data. TECHNICAL MEMORANDUM DRDC Ottawa. 52 pp 1-44.
[4] Vachon P W and Wolfe J. 2008. Validation of ship signatures in Envisat ASAR AP mode data using AISLive. TECHNICAL MEMORANDUM DRDC Ottawa. 5 pp 10-45.
[5] Grasso R, Mirra S, Baldacci A, Horstmann J, Coffin M and Jarvis M. 2009. Performance assessment of a mathematical morphology ship detection algorithm for SAR images through comparison with AIS data. Ninth International Conference on Intelligent Systems Design and Applications. pp 602-607.
[6] Zhao Z, Ji K F, Xing X W and Zou H X. 2012. Research on ship surveillance by integration of space-borne SAR and AIS. China High Resolution Observation to Earth Academic Seminar - Satellite Remote Sensing and Applications. 4-62 pp 5-8.
[7] Myronenko A and Song X (2010) Point Set Registration: Coherent Point Drift. IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE. 32 pp 2262-2273.
[8] Le projet LIMES: Land and Sea Integrated Monitoring For European Security. 22 January 2013. Available online: http://www.slideserve.com/vivek/le-projet-limes-land-and-sea-integrated-monitoring-for-european-security.