Study of data-driven methods for vessel anomaly detection based on AIS data

Ran Yan[1], Shuaian Wang[2]

[1]Department of Logistics and Maritime Studies, Hong Kong Polytechnic University, Hung Hom, Hong Kong
angel-ran.yan@connect.polyu.hk

[2]Department of Logistics and Maritime Studies, Hong Kong Polytechnic University, Hung Hom, Hong Kong
wangshuaian@gmail.com

Abstract

Maritime safety and security are gaining increasing concern in recent years. There are a growing number of studies aiming at improving situation awareness in the maritime domain by identifying vessel anomaly behaviors based on the data provided by the Automatic Identification System (AIS). Two types of data-driven methods are most popular in vessel anomaly detection based on AIS data: the statistical methods and machine learning methods. To improve the detection model efficiency and accuracy, hybrid models are formed by combining different types of methods. In order to incorporate expert knowledge, interactive systems are also designed and realized. In this paper, we provide a review of the popular statistical and machine learning models, as well as the hybrid models and interactive systems based on the data-driven methods used for anomaly detection based on AIS data.

1. Introduction

Maritime transportation plays an important role in the development of the global economy, making maritime safety and security becoming an area of focus [1, 2, 3, 4]. Maritime safety and security are monitored by the widely used surveillance and tracking systems. One of the typical and rapid developing systems is the space-born Automatic Identification System (AIS). The AIS transmitter is compulsive for all passenger ships and all other ships with more than 300 deadweight ton, and it is able to broadcast the static vessel data (including vessel IMO number, vessel name, vessel type, and vessel size, etc.) as well as kinematic vessel data (including vessel position, vessel speed, ship course, and ship heading, etc.) [5]. The historical and live AIS records can be obtained from the Internet sources, including but not limited to Marina Traffic, VT explorer, HIS global, and AIShub. According to the review of Tu et al. on the AIS data quality [5], the commercial AIS data providers can provide accurate ship position information, and most of them can offer necessary vessel kinematic information. However, vessel kinematic information provided by the non-commercial AIS data sources is serious missed, and both the commercial and non-commercial data sources miss the static information of the vessels. Regarding the time resolution of AIS data, which refers to the time interval between two consecutive AIS message and is important for efficient data mining, it is unable to be guaranteed by the data providers.

Although first developed for avoiding ship collision accidents, the AIS data is widely used in the domain of maritime safety, including but not limited to real-time anomaly detection, ship route estimation, ship path planning, and ship and port performance evaluation. In addition, innovative and real-time maritime surveillance systems are also proposed by combining AIS data with visualization technologies.

Vessel anomaly detection is one of the most important application areas of AIS data. The coastal authorities use the anomaly detection systems to identify the nefarious activities, such as piracy, human trafficking, drug smuggling, or abnormal ship sailing. In this paper, we present a review of the data-driven methods that are most widely used in vessel anomaly detection: the statistical methods and machine learning methods, and their combinations. In addition, the interactive systems based on the two methods are also introduced.

2. Literature research method and review structure

To access the related papers, we searched the database of Google Scholar, Web of Science, and Scopus by using the combination of “AIS” and “anomaly detection”, or “AIS” and “abnormal behavior detection” as keyworks. A total of 59 papers were found, including three review papers and 56 research papers. Then, papers using statistical and machine learning methods are chosen, with a total of 34 papers. Among the 34 selected paper, 12 papers adopt statistical methods, 10 papers adopt machine learning methods, 3 papers combine different methods, while 9 papers propose vessel anomaly detection systems. In the rest of the paper, we will make a detailed review of the related papers and give some possible research topics for future research.

3. Data-driven models for vessel anomaly detection

Two types of data-driven methods are widely used in maritime vessel anomaly detection based on AIS data: statistical models and machine learning models [6]. Basically, two steps are composed in the data-driven methods. First, constructing a ship normal behavior model from historical and/or real-time data (i.e., from the training data). Second, matching newly observed vessel data (i.e., the training data) with the learned normalcy model. As the statistical models are constructed based on the assumption that in a stochastic process, normal cases occur with a higher probability than those unnormal cases, observations with a lower probability than the threshold in statistical inference process are considered as anomalous behaviors [7]. While in the machine learning models, testing vessels with properties that deviate from the learned normal model to some certain extent are claimed with abnormal behaviors [8]. By combining different types of methods, hybrid vessel anomaly detection models with better performance can be formed.

3.1. Statistical models for vessel anomaly detection

As a mathematical model based on probability distributions of random variables, statistical models are widely used in maritime vessel anomaly detection [6][7][8]. The main methods include but are not limited to Gaussian process, kernel density estimation, Gaussian mixture model, Bayesian networks and hidden Markov chain.

One mainstream of research using statistical methods develops models based on Gaussian process. In 2011, Will et al. developed a model based on Gaussian process to demonstrate normal shipping behavior constructed from the AIS data. The model could detect the ship abnormal and unsafe behaviors based on ship's speed and location [9]. Smith et al. combined Gaussian process and extreme value theory to detect ship abnormality, in which the extreme value distribution was endowed with vessel dynamic. [10]. Base on this work, Smith et al. proposed another anomaly detection model combing Gaussian process, extreme value theory and divergence measurement. Distribution of vessel dynamic changes and data sample size changes were considered in the combined Gaussian process-extreme value theory (GP-EVT) model for the first time [11].

The kernel density estimation (KDE), which is a purely non-parametric statistical approach, is also used for ship anomaly detection. A simple and fast algorithm based on KDE for predicting the location and velocity of ships was proposed by Ristic et al., which could also be used for ship abnormal behavior detection [12]. On the contrary to the KDE, the Gaussian mixture model (GMM), which is a parametric density estimation model, is also widely used. Laxhammar proposed two unsupervised normal vessel traffic pattern clustering models which were based on the GMM and used Expectation-Maximization (EM) algorithm as the clustering algorithm. One primary model was based on the momentary velocities of the vessel in a two-dimensional plane, while the other was an extension of the primary model which incorporated the momentary position [13]. Some studies have compared the performance of KDE and GMM in ship abnormal behavior detection. Laxhammar et al. adopted a novel performance measure to evaluate and compare the vessel anomaly detection performance of the adaptive KDE and GMM. The results suggested that although KDE was superior in modeling normalcy of the ships, there was no significant difference in KDE and GMM when conducting anomaly detection [14]. Another comparison between the GMM and KDE was made by Anneken et al. By using an annotated dataset of real AIS data, the authors concluded that the false detections and the undiscovered anomalies were high for both algorithms [15]. To improve the detection accuracy, Brax et al. then introduced precise and imprecise anomaly detectors to extend the currently used anomaly detection approach by using Bayesian and credal combination operators [16].

As an easily understandable probabilistic graphical model, Bayesian network (BN) is also used in maritime anomaly detection. Lane et al. proposed a BN to detect the overall threat of the ships based on the identified five common anomalous ship behaviors [17]. In 2014, Mascaro et al. constructed dynamic and static BN models from real AIS data and incorporated information related to weather, time and ship dynamic motion in successive steps. [18]. Apart from Bayesian networks, other methods based on Bayes' theorem are also chosen in anomaly detections. For example, Kowalska put forward a data-driven non-parametric Bayesian model based on Gaussian process. Active learning paradigm was adopted to reduce computational complexity [19].

In addition to the abovementioned statistical methods, models based on other forms of statistical approach are also proposed. For example, a computation method to detect abnormal vessel activities based on density mapping and hidden Markov model (HMM) was proposed by Tun et al. based on AIS data [20]. Smith et al. proposed a multi-class hierarchy framework for different class of ships based on conformal predictors. The model consisted of three levels of artificial classes: Global class for all normal AIS records, Type classes for each vessel type, and Local class for each vessel. As every vessel was treated individually, more abnormal ships could be detected [21].

3.2. Machine learning methods for vessel anomaly detection

As a fast developing approach, machine learning methods are widely adopted in anomaly detection [22]. One typical type is the unsupervised learning methods, which use unlabeled training data to construct the learning model by using clustering algorithms [23]. In contrast to unsupervised learning methods, supervised learning methods use training data with labels to construct the learning model [24].

One typical unsupervised approach used in vessel anomaly detection is the density-based spatial clustering of applications with noise (DBSCAN) data clustering algorithm, which was first proposed by Ester et al. [25]. When applied to maritime anomaly detection, Pallotta et al. proposed a methodology named Traffic Rout Extraction and Anomaly Detection (TREAD) based on DBSCAN. The methodology was used to learn a statistical model from AIS data in an unsupervised way in order to turn the raw AIS data to information supporting decisions [26, 27]. Pallotta et al. further improved the TREAD methodology by using hierarchical reasoning. Based only on the positional information obtained from raw AIS data, the off-route vessels, which referred to the vessels that were not following an existing route, were first detected [28]. For those on-route vessels, ships with heading anomaly and speed anomaly were also identified. Liu et al. put forward an extended DBSCAN called DBSCANSD taking ship speed and direction as non-spatial attributes into consideration. Then, an algorithm to extract normal ship stopping areas was proposed to identify the ship moving and stopping areas [29]. Based on the clustering results of this work, Liu et al. extended the model into three division distances by considering longitude, latitude, speed and direction to Improve detection accuracy [30]. As another extension of DBSCAN, Radon et al. proposed a three-layer framework called MADCV combining weather information as “context information” to filter false alarms. Empirical studies using AIS data suggested that this approach could adapt to new contextual information [31].

Apart from DBSCAN, other unsupervised clustering methods were also included in the studies on anomaly detection. For example, a framework named MT-MAD, which was short for Maritime Trajectory Modeling and Anomaly Detection was proposed by Lei. As the name suggested, the model contained two parts: one for unsupervised maritime trajectory modeling and the other for anomaly detection. Experimental results on real AIS data showed that the proposed framework was effective in detecting maritime anomalous movement behaviors [32].

Other forms of unsupervised machine learning methods were also proposed based on AIS data. Vespe et al. proposed an unsupervised approach to learn ship motion patterns by creating ship waypoint graph, which contained vessel objects, turning point, ports and offshore platforms, entry or exit point, sea lane, and route. [33]. Guillarme and Lerouvreur proposed a probabilistic based normalcy model of vessel dynamics learned in an unsupervised way. The model had two levels and mainly contained three parts: trajectory partitioning, clustering and path modeling. The two-scale model could be used for anomaly detection, AIS consistency analysis, and ship path prediction [34].

3.3 Hybrid models for vessel anomaly detection

Hybrid models for vessel abnormal behavior detection are formulated by combining different forms of methods or combining the numerical models with expert knowledge to improve the prediction accuracy. Nevertheless, the hybrid models are not easy to be implemented due to its complicated format. By counteracting the drawbacks of different models, several studies have developed high performance models for vessel anomaly detection based on AIS data. De Vries and van Someren proposed a machine learning network to perform tasks including ship trajectories clustering, classification and outlier detection. There were three steps in the approach. First, a piecewise linear segmentation method was adopted to compress trajectories. Second, a similarity-based approach based on kernel methods was applied for detection tasks of clustering, classifying and outlier. Finally, geographical domain knowledge was integrated with the framework [35]. Smith et al. described conformal prediction techniques for maritime anomaly detection. First, an unsupervised conformal anomaly detection framework was proposed under the criteria of the average *p*-value. Then, two supervised non-conformity measures were adopted: one was based on KDE, and the other was based on k-nearest neighbors (k-NN) algorithm as a comparison. After that, AIS data was used to test the performance of the non-conformity models with average *p*-value as a criterion. The results indicated that KDE performed better than k-NN as a non-conformity measure with the data set [36]. Wang et al. presented a two-level approach for vessel abnormal routes detection. First, an unsupervised model named DBSCANSD which was proposed by Liu et al. [29] was applied for data points pre-clustering. Then, combined with the expert knowledge, optimal labeling results of the data points (normal or abnormal) were generated. Second, a supervised learning model was trained by generated labeled data to detect the anomaly of new-coming vessels [37].

4. Interactive systems for vessel anomaly detection

As the detection of ship anomalous behaviors is a complicated problem, especially when confronting the rare and ambiguous situations, support and guidance from the domain experts are beneficial to the detection process [38]. By applying interactive and visualization technologies, expert judgment and decision can be comprised in the vessel anomaly detection systems.

The basis of one typical ship anomaly detection system was laid by a study conducted by Rhodes et al., in which a learning model comprising an unsupervised clustering algorithm and a supervised labeling and mapping algorithm were proposed. Both the vessel routine behaviors and abnormal behaviors were learned by these cognitively inspired algorithms [39]. To improve the performance of the proposed system, neuro-biologically inspired algorithms were added for better adapting to the evolving situations [40]. Then, an improved neuro-biologically inspired algorithm consisting of real-time tracking information and with the ability of learning motion patterns was proposed by Rhodes et al. Weights were added to the learned model, which enabled better ship location prediction performance [41]. In order to combine user knowledge in the anomaly detection system, an interactive approach to combine expert knowledge and normal behavior models was proposed by Riveiro et al. The approach was implemented on an anomaly detection prototype called VISAD [38]. Then, Riveiro et al. gave an overview introduction of VISAD, in which expert knowledge was inserted and the detection procedure was transparent to the users [42]. Another surveillance system called SeeCoast was illustrated by Rhodes et al. In SeeCoast, vessel track classification information was generated based on the video streams provided by USCG cameras. Then, a coherent track picture was generated according to the AIS data and surface surveillance radars. Based on the track picture, the unsafe, illegal, and threatening vessel activities could be identified using machine learning methods [43]. Other similar systems, such as the satellite-extended-vessel Traffic Service (SEV) system [44] and distributed multi-hypothesis tracking (DMHT) technology-based trackers [45] were also designed, introduced and analyzed in the literature.

5. Future research opportunities

The access to shipping AIS data makes it possible to apply statistical and machine learning methods to maritime anomaly detection. Undoubtedly, the application of AIS data to vessel abnormal behavior detection will receive more attention in the future. In this section, we will provide some future research topics on maritime anomaly detection based on AIS data.

First, most of the abovementioned papers aim to focus on offline anomalous detection, i.e., using the historical AIS data to construct the detection models and test the performance of the detection models. As online anomalous vessel behavior detection is not allowed, implementation of the proposed frameworks and models will be hindered. Therefore, one possible research area is developing real-time detection algorithms and systems to identify online vessel abnormal behaviors. Second, most of the models designed for vessel anomaly detection only consider the vessel kinematic attributes, such as the vessel speed over ground, vessel course over ground and vessel location information. However, vessel static factors, including vessel type, vessel size, vessel flag, vessel company and non-vessel factors, including the regional traffic density, local weather conditions, regional policies and regulations will also have an impact on the vessel behaviors. Taking those factors into consideration when constructing the normal behavior models may help improve the detection accuracy. Third, the performance of the detection ability of the models is largely dependent on the quality of AIS data. However, there are some inaccuracies and errors occurring in the data, especially the manually entered data such as ship's length, IMO number, name, call sign, etc. Moreover, not all ships are equipped with or properly operate the AIS system, so not all ships can be well detected. Thus, combining different sources of data, including but not limited to Long Range Identification and Tracking of ships (LRIT), Synthetic Aperture Radar (SAR), sensors like sonar and thermal infrared, as well as identifying and filtering incorrect AIS data [45], can help refine the input data, thus improving the performance of the detection models.

6. References

[1] Weng, J., Yang, D., Qian, T. and Huang, Z. Combining zero-inflated negative binomial regression with MLRT techniques: an approach to evaluating shipping accident casualties, *Ocean Engineering*, Vol. *166*, pp. 135-144, (2018)

[2] Weng, J., Meng, Q. and Qu, X. Vessel collision frequency estimation in the Singapore Strait, *The Journal of Navigation*, Vol. *65, No.* 2, pp. 207-221, (2012)

[3] Li, S., Meng, Q., and Qu, X. An overview of maritime waterway quantitative risk assessment models, *Risk Analysis: An International Journal*, Vol. *32, No.* 3, pp. 496-512, (2012)

[4] Qu, X., Meng, Q., and Li, S. Ship collision risk assessment for the Singapore Strait, *Accident Analysis & Prevention*, Vol. *43, No.*6, pp. 2030-2036, (2011)

[5] Tu, E., Zhang, G., Rachmawati, L., Rajabally, E. and Huang, G. B. Exploiting AIS data for intelligent maritime navigation: a comprehensive survey from data to methodology, in Proceedings of IEEE Transactions on Intelligent Transportation Systems, Vol. 19, No. 5, pp. 1559-1582, (2018)

[6] Mark Smith. Anomaly detection in vessel track data. (Thesis submitted for the degree of Master of Science (Research)). Accessed December 2018 from http://www.robots.ox.ac.uk/~parg/pubs/theses/markSmithMScThesis2014.pdf

[7] Anscombe, F. J. Rejection of outliers, Technometrics, Vol. 2, No. 2, pp.123-146, (1960)

[8] Sidibé, A. and Shu, G. Study of automatic anomalous behavior detection techniques for maritime vessels, The Journal of Navigation, Vol. 70, No. 4, pp. 847-858, (2017)

[9] Will, J., Peel, L. and Claxton, C. Fast maritime anomaly detection using kd-tree gaussian processes, in Proceedings of IMA Maths in Defence Conference, (2011)

[10] Smith, M., Reece, S., Roberts, S. and Rezek, I. Online maritime abnormality detection using gaussian processes and extreme value theory, in Proceedings of IEEE 12th International Conference on Data Mining, pp. 645-654, (2012)

[11] Smith, M., Reece, S., Roberts, S., Psorakis, I. and Rezek, I. Maritime abnormality detection using Gaussian processes, Knowledge and information systems, Vol. 38, No. 3, pp. 717-741, (2014)

[12] Ristic, B., La Scala, B. F., Morelande, M. R. and Gordon, N. J. Statistical analysis of motion patterns in AIS Data: Anomaly detection and motion prediction, FUSION, pp. 1-7, (2008)

[13] Laxhammar, R. Anomaly detection for sea surveillance, in Proceedings of 2008 11th IEEE International Conference on Information Fusion, pp. 1-8, (2008)

[14] Laxhammar, R., Falkman, G. and Sviestins, E. Anomaly detection in sea traffic-a comparison of the gaussian mixture model and the kernel density estimator, in Proceedings of IEEE 2009 12th International Conference on Information Fusion, pp. 756-763, (2009)

[15] Anneken, M., Fischer, Y. and Beyerer, J. Evaluation and comparison of anomaly detection algorithms in annotated datasets from the maritime domain, in Proceedings of IEEE SAI Intelligent Systems Conference, pp. 169-178, (2015)

[16] Brax, C., Karlsson, A., Andler, S. F., Johansson, R. and Niklasson, L. Evaluating precise and imprecise state-based anomaly detectors for maritime surveillance, in Proceedings of IEEE 2010 13th International Conference on Information Fusion, pp. 1-8, (2010)

[17] Lane, R. O., Nevell, D. A., Hayward, S. D. and Beaney, T. W. Maritime anomaly detection and threat assessment, in Proceedings of IEEE 2010 13th International Conference on Information Fusion, pp. 1-8, (2010)

[18] Mascaro, S., Nicholso, A. E. and Korb, K. B. Anomaly detection in vessel tracks using Bayesian networks, International Journal of Approximate Reasoning, Vol. 55, No. 1, pp. 84-98, (2014)

[19]Kowalska, K. and Peel, L. Maritime anomaly detection using Gaussian process active learning, in Proceedings of IEEE 2012 15th International Conference on Information Fusion, pp. 1164-1171, (2012)
[20]Tun, M. H., Chambers, G. S., Tan, T. and Ly, T. Maritime port intelligence using AIS data, Recent advances in security technology, pp. 33-43, (2007)
[21]Smith, J., Nouretdinov, I., Craddock, R., Offer, C. and Gammerman, A. Conformal anomaly detection of trajectories with a multi-class hierarchy, International symposium on statistical learning and data sciences, pp. 281-290, (2015)
[22]Zhou, M., Qu, X. and Li, X. A recurrent neural network based microscopic car following model to predict traffic oscillation, Transportation Research Part C. Vol. 84, pp. 245-264, (2017)
[23]Hastie, T., Tibshirani, R. and Friedman, J. Unsupervised learning, Springer Press, New York (2009), pp. 485-585
[24]Jordan, M. I. Supervised learning and systems with excess degrees of freedom, (1988)
[25]Ester, M., Kriegel, H. P., Sander, J. and Xu, X. A density-based algorithm for discovering clusters in large spatial databases with noise, ACM Knowledge Discovery and Data Mining, Vol. 96, No. 34, pp. 226-231, (1996)
[26]Pallotta, G., Vespe, M., and Bryan, K. Vessel pattern knowledge discovery from AIS data: A framework for anomaly detection and route prediction, Entropy, Vol.15, No. 6, pp. 2218-2245, (2013)
[27]Pallotta, G., Vespe, M., and Bryan, K. Traffic knowledge discovery from AIS data, in Proceedings of IEEE 2013 16th International Conference on Information Fusion (FUSION), pp. 1996-2003, (2013)
[28]Pallotta, G., and Jousselme, A. L. Data-driven detection and context-based classification of maritime anomalies, in Proceedings of IEEE 2015 18th International Conference on Information Fusion (Fusion), pp. 1152-1159, (2015)
[29]Liu, B., de Souza, E. N., Matwin, S. and Sydow, M. Knowledge-based clustering of ship trajectories using density-based approach, in Proceedings of IEEE 2014 International Conference on Big Data, pp. 603-608, (2014)
[30]Liu, B., de Souza, E. N., Hilliard, C. and Matwin, S. Ship movement anomaly detection using specialized distance measures, in Proceedings of IEEE 2015 18th International Conference on Information Fusion (Fusion), pp. 1113-1120, (2015)
[31]Radon, A. N., Wang, K., Glässer, U., Wehn, H. and Westwell-Roper, Contextual verification for false alarm reduction in maritime anomaly detection, in Proceedings of IEEE 2015 International Conference on Big Data, pp. 1123-1133, (2015)
[32]Lei, P. R. A framework for anomaly detection in maritime trajectory behavior, Knowledge and Information Systems, Vol. 47, No. 1, pp. 189-214, (2016)
[33]Vespe, M., Visentini, I., Bryan, K. and Braca, P. Unsupervised learning of maritime traffic patterns for anomaly detection, in Proceedings of 9th IET Data Fusion and Target Tracking Conference, pp. 1-5, (2012)

[34] Le Guillarme, N. and Lerouvreur, X. Unsupervised extraction of knowledge from S-AIS data for maritime situational awareness, in proceedings of 2013 16th International Conference on Information Fusion (FUSION), pp. 2025-2032, (2013)
[35] De Vries, G. K. D. and Van Someren, M. Machine learning for vessel trajectories using compression, alignments and domain knowledge, Expert Systems with Applications, Vol. 39, No. 18, pp.13426-13439, (2012)
[36] Smith, J., Nouretdinov, I., Craddock, R., Offer, C. and Gammerman, A. Anomaly detection of trajectories with kernel density estimation by conformal prediction, in proceedings of IFIP International Conference on Artificial Intelligence Applications and Innovations, pp. 271-280, (2014)
[37] Wang, X., Liu, X., Liu, B., de Souza, E. N. and Matwin, S. Vessel route anomaly detection with Hadoop MapReduce, in proceedings of IEEE International Conference on Big Data, pp. 25-30, (2014)
[38] Riveiro, M. and Falkman, G. Interactive visualization of normal behavioral models and expert rules for maritime anomaly detection, in proceedings of 2009 Sixth International Conference on Computer Graphics, Imaging and Visualization, pp. 459-466, (2009)
[39] Rhodes, B. J., Bomberger, N. A., Seibert, M. and Waxman, A. M. Maritime situation monitoring and awareness using learning mechanisms, in proceedings of IEEE Military Communications Conference, pp. 646-652, (2005)
[40] Bomberger, N. A., Rhodes, B. J., Seibert, M. and Waxman, A. M. Associative learning of vessel motion patterns for maritime situation awareness, in proceedings of 2006 9th International Conference on Information Fusion, pp. 1-8, (2006)
[41] Rhodes, B. J., Bomberger, N. A. and Zandipour, M. Probabilistic associative learning of vessel motion patterns at multiple spatial scales for maritime situation awareness, in proceedings of IEEE 2007 10th International Conference on Information Fusion, pp. 1-8, 2007
[42] Riveiro, M., Falkman, G., Ziemke, T., and Warston, H. VISAD: an interactive and visual analytical tool for the detection of behavioral anomalies in maritime traffic data, Visual Analytics for Homeland Defense and Security, Vol. 7346, (2009)
[43] Rhodes, B. J., Bomberger, N. A., Freyman, T. M., Kreamer, W., Kirschner, L., Adam, C. L., Mungovan, I. W., Stauffer, C., Stolzar, L., Waxman, A. M. and Seibert, M. SeeCoast: persistent surveillance and automated scene understanding for ports and coastal area, Defense Transformation and Net-Centric Systems, Vol. 6578, (2007)
[44] Vespe, M., Sciotti, M., Burro, F., Battistello, G. and Sorge, S. Maritime multi-sensor data association based on geographic and navigational knowledge, In proceedings of IEEE 2008 Radar Conference, pp. 1-6, (2008)
[45] Carthel, C., Coraluppi, S. and Grignan, P. Multisensor tracking and fusion for maritime surveillance, in proceedings of IEEE 2007 10th International Conference on Information Fusion, pp. 1-6, (2007)