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Knowledge-based AIS Shadow Zone Identification in VTS Area

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Abstract
The current lack of reliability for AIS messages is a key disadvantage for their trustworthiness as a navigational device. AIS messages are frequently lost in the VTS area. This paper is concerned with identifying the AIS shadow zone in the VTS area. We proposed a knowledge-based algorithm to extract sequential messages from raw data. After extracting data for more than 2 knots from raw data for an underway vessel, loss rate is calculated from the data within 10 minutes of the reporting intervals. The first row in each group is discarded to use sequential messages. The loss message is visualized by density contour plots with two-dimensional histograms. Two and three shadow zones were identified for AIS Class-A type and B-type, respectively, in Wando VTS. It is possible to check which zone is more frequently lost visually. Furthermore, the analysis shows that the loss rate of the Class-B type was 33 times that of the Class-A type. It was found that the loss rate of AIS is mainly caused by fishing vessels with lower antenna height than cargo ships and passenger ships. In particular, it was found that the loss rate of fishing vessels equipped with Class-B type was about 10 times that of those with Class-A type. We also found a weak correlation between number of message and loss message. Therefore, the VTS operator should recognize the characteristics of AIS message loss rate by ship type through these findings, and rate trustworthiness of AIS predicted messages accordingly. If there are any obstructions such as islands or mountains in the VTS area, the proposed method allows for easy identification of relative AIS shadow zone.

Keywords: *Shadow zone, AIS, VTS, Identification, Loss rate.*

1. Introduction

An automatic identification system (AIS) allows for transmitting messages between AIS devices, which can be installed on vessels and base stations. Compared with the functions of radar, AIS provides dynamic (e.g., longitude, latitude, course, heading, speed) and static (e.g., MMSI, name, call sign, length, breadth, vessel type) data in real time [1]. AIS can detect other equipped targets in situations where radar detection is limited such as behind islands, around bends and in conditions of restricted visibility [2,3]. The International Maritime Organization (IMO) thus passed a mandate in 2002 that vessels needed AIS installed to aid safety and identification [4].

There are two different types of AIS transceivers available: Class-A type AIS (mandatory equipment) and Class-B type (optional, for smaller vessels). Class-A type AIS is designed to translate into a maximum range of ~200 Nautical Miles (NM), but the radio frequency coverage is typically 20 NM for vessel-to-vessel and 40 NM for vessel-to-shore base station [5].

The AIS has played a crucial role in improving safety at sea since the introduction, enhancing traffic management for vessels. The AIS information has been used for various purposes such as researching accident investigation [6,7], maritime risk models [8-11], collision avoidance maneuvers [12-14], vessel trajectory analysis

[15], anomaly detection [16,17], and vessel domain analysis [18,19].

AIS has the potential to be a helpful navigational aid if correctly used. However, not all vessels accurately report all AIS information. AIS units may not always be installed following the IMO Guidelines. There are thus errors in the static data as well as the dynamic data, and voyage-related data [19,20]. Thus, it is essential that AIS data be reliable and their integrity is ensured. The poor performance and transmission of inaccurate information by AIS are essential issues that can affect its usefulness [19].

Therefore, the reporting interval according to the International Telecommunications Union (ITU) standard is crucial when implementing prediction algorithms [3]. However, AIS message losses, caused by reporting intervals often not being kept, have been confirmed by several studies. Approximately 42% of all vessels do not conform to the reporting intervals described in ITU [21]. In addition, such a lower update rate would negatively affect decision making for Vessel Traffic Services (VTS). AIS information gives many valuable navigational benefits to VTS. The received AIS data can be used in algorithms to implement automatic approaches for collision avoidance and to predict vessel's location at VTS [15]. Due to exceeding reporting intervals, the AIS system is insufficient as a standalone source of information for collision avoidance and continuous vessel monitoring in real-time applications [3,21]. Because of AIS lost messages, research was also carried out for interpolation [22,23]. However, the reliability of the predictive value obtained by interpolation becomes worse as the loss time increases.

While interpolating the AIS data is essential, identifying which areas are ultimately shadowed is also important. This is because those interpolations were affected by the shadow zones as well [24]. There have been many studies on the identification of radar shadow zones [25,26]. However, there have been few studies conducted to identify AIS shadow zones. Previous research [24] shows the overall distribution of the AIS coverage, however, the methods did not focus on identification shadow zones of AIS. The output of the research displayed the density grid based on vessel tracks. If the vessels cannot navigate due to presence of aquaculture farms or low depth of the sea in a particular area, no AIS data naturally is collected. There is a possibility that it is misjudged as shadow zones because there is little ship traffic. Therefore, a method for identifying AIS shadow zone is required even in areas with high vessel traffic volume.

This study proposes a method to identify the shadow zone of AIS based on the vessel traffic trajectories. In addition, we analyze loss rate by the hour and visualize density scatterplots as two-dimensional histograms for Class-A type and B-type. The remainder of paper is organized as follows. The data sources, data preparation, and methods are presented in Section 2. Section 3 presents the results and the discussion. Section 4 concludes the paper.

2. Materials and Methods

2.1. Study Area

Wando County in South Korea is the study area. There is a national marine park in the coastal waters of Wando. Wando County accounts for 80% of the abalone aquaculture farms in South Korea. There are thus numerous fishing vessels in this area. The study area is located between latitudes 33.95° - 34.33°N and longitudes 126.36° - 127.10°E, with an area of approximately 2,853 km^2 [Figure 1]. The upper area is the coastal sea of Wando, and the lower area is the open sea, is also a major shipping area in the world, linking major economies such as Russia, Japan, China, and South Korea.

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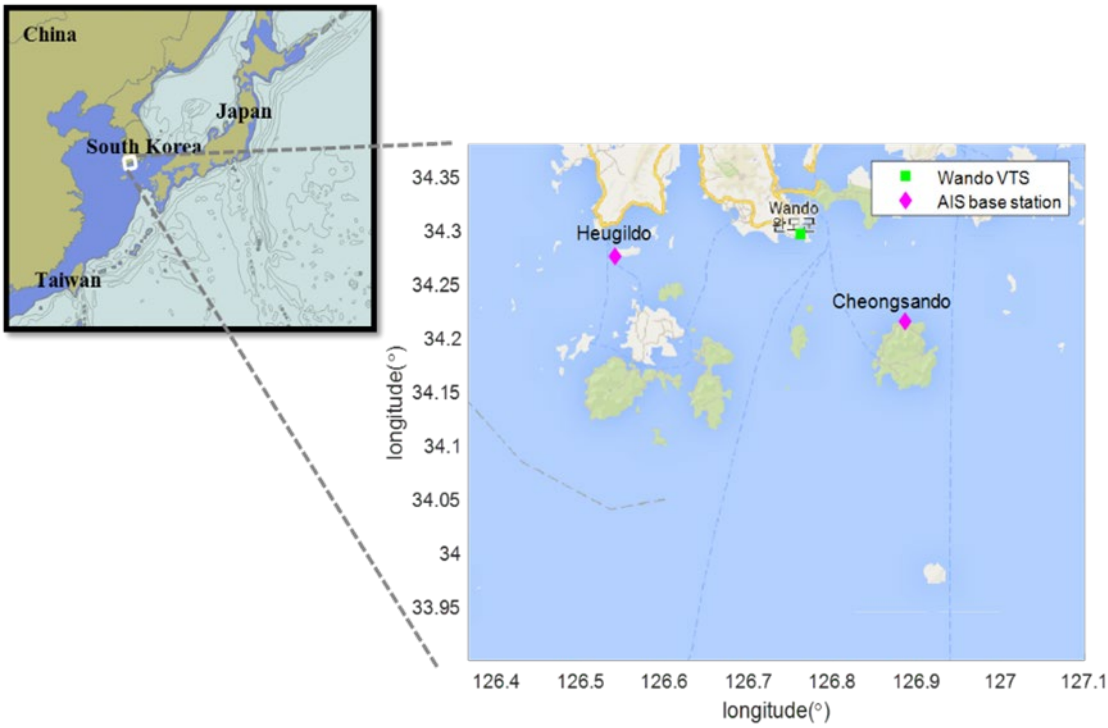

Figure 1. Study area with two AIS base stations and Wando VTS

2.2. AIS Datasets

Forty-two AIS base stations were built on the South Korean coasts between 2001 and 2008. There are two AIS base stations, Heugildo Island and Chengsando Island, in the study area. The AIS base stations used by the Wando VTS are located at sites to ensure coverage of the VTS surveillance area. The exact location of AIS base station is 34° 12.91′N, 126°53.17′E at Chengsando Island, and 34°16.54′N, 126°32.43′E at Heugildo Island (Figure 1). The data used in this study were reported from June 1 to June 9, 2018. The dataset includes Class-A type as well as Class-B type AIS messages. AIS data were collected from a total of 328 vessels in the Wando VTS. Class-A type AIS data were collected from 236 vessels, including 54 fishing vessels, 159 cargo vessels, and 23 passenger vessels. Class-B type AIS data were collected from 92 vessels, including 63 fishing vessels and 29 leisure fishing boats. The dataset consisted of a colossal amount of dynamic and static information. The MMSI and vessel type among the static data is used for sorting, and the dynamic data is used for the identification of AIS shadow zones. The database comprises about 1 million datasets for Class A dynamic messages and 140 thousand datasets for Class-B type dynamic messages. Class-B type messages are below 13.4% compared to Class-A type.

2.3. Data Analysis Approach

In the first step, the preprocessing of datasets is conducted. The seven AIS variables (MMSI, vessel type, date, time, longitude, latitude, speed) were chosen for the analysis. It is because that the variables, including the longitude, latitude, and speed, are rare in terms of error values, as compared to vessel heading [27]. AIS message errors regarding the vessel type [19] were corrected using data released by the ITU [11,28] and the port management information system (Port-MIS) data of South Korea. Then, AIS messages sent from positions outside the study area were discarded. The raw data were classified into AIS Class type and vessel type.

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In the second step, criteria were set for AIS loss message. It is necessary to know the properties and transmission periods of Class-A type and Class-B type. AIS-equipped vessels periodically broadcast position data. The Class-A type broadcast dynamic data very frequently, at 2–10 seconds intervals depending on the vessels speed while underway. Whereas Class-B type has longer reporting intervals than Class-A type. Vessels going less than 2 knots transmit dynamic data every 3 minutes, while vessels are navigating more than 2 knots updates dynamic data every 30 seconds at Class-B type. This study attempts to find the shadow zone in the vessel underway. Therefore, in this study, at least two consecutive dynamic data were extracted with a speed of 2 knots or more. It is because that when Class-B type vessels are navigating with more than 2 knots, they should update dynamic data every 30 seconds.

In the third step, the reporting interval ($\varDelta$) with the date and time variable in each dynamic data was calculated in seconds. We use the following settings and notations: A vessel trajectory is expressed as $R = (p_1,\ p_2, \ldots,\ p_n)$ in a sequence of positions, where p_k is the position of index k, and n is the number of indices . $\varDelta$ is measured between two sequenced vessel positions, $\varDelta = t_{k+1} - t_k$, where t_k indicates the time at which a vessel is at position p_k. Then, the criterion of $\varDelta$ was set for analysis. We assume that data exceeding the threshold is a message loss caused by the forced power down. Fishing vessels and leisure fishing boats equipped with Class A- or B-type are reluctant to position exposure due to the nature of their operation. Hence, the AIS power is frequently forcibly cut off, and dynamic data loss occurs frequently. That is why, in this study, we assume 10 minutes (= 600 seconds) as the threshold value, and only the data with $\varDelta$ of less than 10 minutes was used as the analytical data. Therefore, if there is $\varDelta$ of more than 10 minutes in the extracted data, it should be separated into another group. Then the first row in each group is deleted because it does not include sequence data and no $\varDelta$ can be calculated. The data from each group is agglomerated to form the final data output.

In the fourth step, the AIS loss rate (r) is calculated. According to the previous research [29], the average $\varDelta$ of AIS Class-A type and B-type for all vessels is less than 180 seconds. Therefore, in this study, if the $\varDelta$ is less than 180 seconds, that was defined as normal messages, and as loss message (l) otherwise. r is defined as [30]:

$$r = \frac{l}{N} \tag{1}$$

where l is the number of AIS lost message, N is the number of messages, it means that the sum of normal messages and loss messages, r, is the loss rate in the area. The following procedure is a processing to extract the AIS loss and normal messages [Table 1].

In the last step, the shadow zone of AIS base station is identified by visualization. A full loss positions (p^{loss}) needs to provide the two-dimensional nature of the data. We thus conducted analyses in the two-dimensional histogram. Density contour plots with smooth histograms [31]. The data were binned on a 200 × 200 grid. A large number of measurements can be taken (in this case about 40,000 individual particles), resulting in a relatively dense area. p^{loss} events in each bin were counted to construct a two-dimensional histogram, and then p^{loss} values are visualized by enhancing smooth density scatterplots. Logarithmically spaced colored contours of the p^{loss} are plotted after smoothing with a two-dimensional second-order difference matrix. We used the jet color map in this implementation, where dark red - brown represents the highest density values and blue represents the lowest density values.

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Table 1. The pseudocode for extracting loss message for AIS

Algorithm extracting loss message for AIS

```
input:   p[1 ... n]  for positions p_1, p_2, ..., p_n
         t [1 ... n]  for time at each position
         s [1 ... n]  for speed at each position
output:  p^loss  for position at loss message
         t^loss  for time at loss message
         p^normal  for position at normal message
         t^normal  for time at normal message
begin
    initialize empty vector members
    initialize empty vector groups
    initialize empty vector agglomerated_data
    for m = 1 to number of vessels
        for k = 1 to n
            Δ ← t_{k+1} − t_k
            s ← s_k
            append k to members
            if s < 2 knots then
                if row size of members ≥ 2 then
                    delete first and last elements of member
                    append members to groups
                end if
                clear members
                append k to members
            end if

            if Δ > 600 seconds then
                if row size of members ≥ 2 then
                    delete first and last elements of member
                    append members to groups
                end if
                clear members
                append k to members
            end if
        end for

        for g=1 to number of groups
            members ← groups [g]
            append data [p, t, Δ] with indices in members to agglomerated_data
        end for
    end for

    if Δ in the agglomerated_data ≤ 180 seconds then
        normal message (p^normal, t^normal)
    else
        loss message (p^loss, t^loss)
    end if
```

3. Results

3.1. AIS Loss Rate

Table 2 shows the number of loss message in comparison with the number of normal messages, and the r by the AIS Class type and vessel type. It was found that the r of Class-B type was 33 times that of the Class-A type. In analysis by vessel type, the r of the fishing vessels equipped with Class-B type was the highest, followed by the leisure vessel. In case of the same fishing vessels, the r is 0.13% when the Class-A type is equipped and 1.32% when the Class-B type is equipped, which is about ten times higher. The r of cargo vessels and passenger vessels is relatively much lower than fishing vessels' and leisure fishing boats'.

Figure 2 is the number of messages and the r of Class-A type and B-type by the hour. The number of messages of Class-A type was 81,109 in 0900–1000h at the highest. On the other hand, the time period with high r was 1400h-1500h (Figure 2(a)). The number of messages of Class-B type was shown as 11,440 (8.2%) in 0600h-0700h at the highest. On the other hand, the time period with high r was 2300–2400h (Figure 2(b)). It may be considered that if there are many messages due to the AIS slot overload at a certain time, there are many loss messages at that time [21]. However, it was found that there is a moderate correlation (0.64) between them for Class-A type and a low correlation (-0.31) for Class-B type.

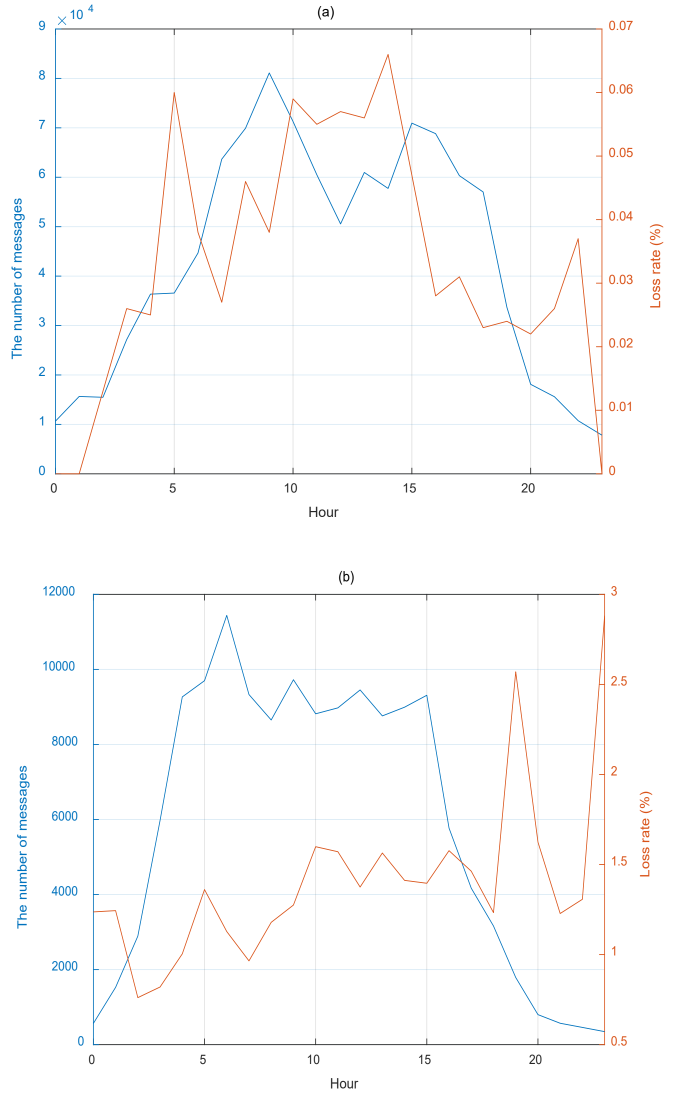

Figure 2. The number of messages and the loss rates of AIS Class-A type (a) and B-type (b) by the hour

Table 2. The number of loss messages in comparison with the number of normal messages, and the loss rate by the AIS Class type and vessel type

AIS Class type	Vessel type	Number of loss messages	Number of normal messages	Loss rate (r)
Class A	Fishing vessels	391	293,612	0.13%
	Cargo vessels	14	246,542	0.01%
	Passenger vessels	12	504,795	0.00%
	Total	417	1,044,949	0.04%
Class B	Fishing vessels	1,611	120,247	1.32%
	Leisure fishing boats	235	18,357	1.26%
	Total	1,846	138,604	1.31%

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3.2. AIS Shadow Zone

As shown in Figure 3, the trajectories of vessels and density scatterplots were superimposed as two-dimensional histograms for loss message by the AIS class type. Two shadow zones were identified for AIS Class-A type (Figure 3(a)). On the other hand, three shadow zones were identified for AIS Class-B type (Figure 3(b)). The shadow zones number ① and ② are due to the altitude of the islands. The distance from Chengsando AIS base station to shadow zone number ② is 4.6 NM and to shadow zone number ③ is 8.3 NM. This is because that the central altitude of Chengsando Island is 350 m. The altitude of Chengsando AIS base station is just 70 m. That is why AIS loss occurs frequently in shadow zone number ② due to the interference of altitude. Therefore, it is necessary to install the antenna of AIS base station at a high altitude position, or provide additional installations.

3.3. Discussion

The VTS monitoring area contains complex geospatial areas, such as many islands. The AIS can detect vessels behind islands and coverage is typically 40 NM for a vessel-to-shore base station [3,5]. However, it was found that the coverage of AIS base station depends on the obstruction of islands and mountains. Class-A type transmit at 12.5 watts. Class-B type is simpler, and lower cost than Class-A- type. Class-B type transmission power is restricted to 2 watts [32]. The lower transmission power means that the coverage of Class-B type is significantly less than that of Class-A type. Therefore, the AIS message updates for Class-B type are broadcast less often than Class-A type. In particular, the AIS Class-B type of South Korea accounted for 46%. That is why, the VTS operator should know the AIS shadow zone in the monitoring area to provide correct information for collision avoidance.

VTS operator must not assume that the collision avoidance solutions proposed by the AIS predicted position are necessarily accurate or correct. High reporting intervals make it challenging to predict vessel movements in real-time, since the state of a vessel is continuously changing with increasing or decreasing speed, performing course correction, etc. A reliable prediction is not possible in this case, since the uncertainty of a predicted vessel state increases over time. Given a complex geospatial area in the VTS, the AIS shadow zone analysis should be preceded. If the AIS message is lost

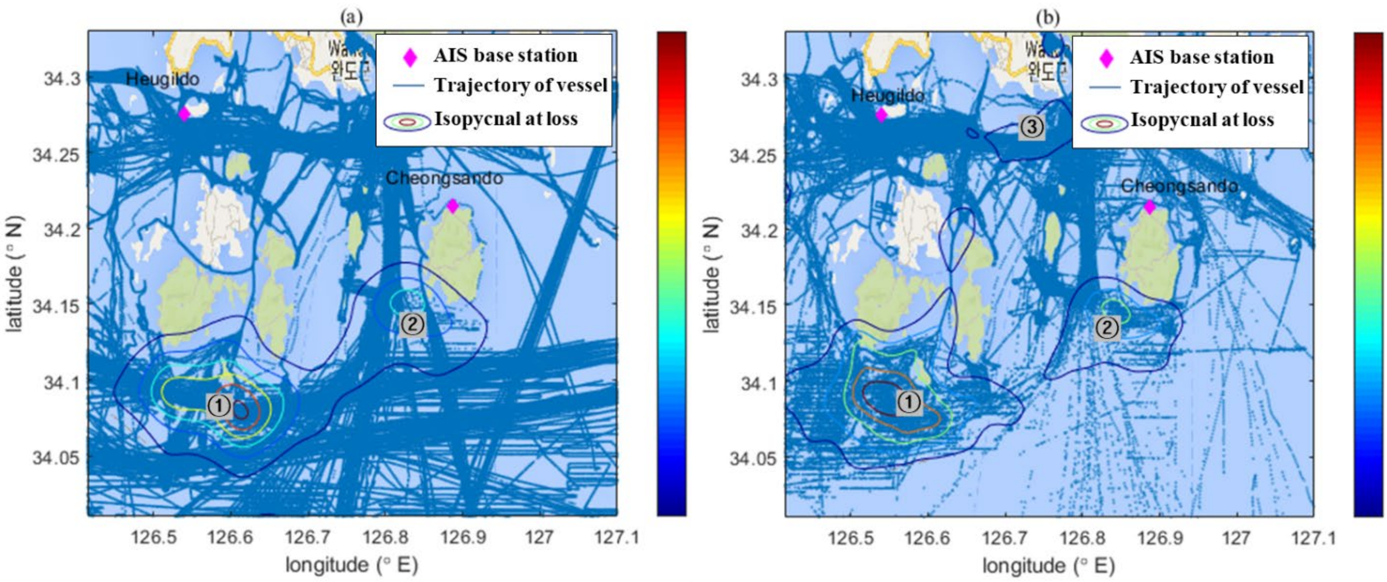

Figure 3. The trajectories of vessels and density scatterplots as two-dimensional histograms for loss message by the AIS Class type. (a) AIS Class-A type. (b) AIS Class-B type

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while the ship is sailing, it may be considered that an overturn accident has occurred due to bad weather. However, it is necessary to keep in mind that the AIS message can be a loss due to AIS shadow zone. The VTS operator must always remember that AIS is just one of the several tools available. AIS is not reliable in many cases; therefore, VTS operators cannot wholly trust the AIS predicted messages. AIS information therefore has to be cross-checked with data from other sources, such as radar and visual observations.

4. Conclusion

The purpose of this study is to identify the shadow zone of AIS based on vessel trajectories. The result of the analysis is that the r of Class-B type was 33 times that of Class-A type. Furthermore, it was found that the r of the fishing vessels with equipped the Class-B type was about 10 times higher than that of the Class-A type. The proposed method enables easy recognition of relative AIS shadow zone in VTS and can be applied to any VTS area.

Further study is required for the research of the message interpolation technique for each shadow zone characteristic is needed. Supported by these further studies, the ship collision prediction and ship safety management of the VTS operator will be improved. Enforcement of quality of AIS message by the further study would improve its efficiency in VTS.

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References

[1] Kao SL, Lee KT, Chang KY, Ko MD. A fuzzy logic method for collision avoidance in vessel traffic service. *The Journal of Navigation*. 2007 Jan;60(1):17–31.

[2] Ou Z, Zhu J. AIS database powered by GIS technology for maritime safety and security. *The Journal of Navigation*. 2008 Oct;61(4):655–65.

[3] Last P, Hering-Bertram M, Linsen L. How automatic identification system (AIS) antenna setup affects AIS signal quality. Ocean Engineering. 2015 May;100:83–9.

[4] International Maritime Organisation (IMO). Guidelines for the Onboard Operational Use of Shipborne Automatic Identification Systems (AIS). Assembly 22nd Session, Resolution 917. 2002 [cited 2019 Feb 21]. Available from: http://www.imo.org/en/KnowledgeCentre/IndexofIMOResolutions/Assembly/ Documents/A.917(22).pdf

[5] Eriksen T, Høye G, Narheim B, Meland BJ. Maritime traffic monitoring using a space-based AIS receiver. *Acta Astronautica*. 2006 May;58(10):537–49.

[6] Wang Y, Zhang J, Chen X, Chu X, Yan X. A spatial–temporal forensic analysis for inland–water ship collisions using AIS data. *Safety Science*. 2013 Aug;57:187–202.

[7] Bye RJ, Aalberg AL. Maritime navigation accidents and risk indicators: An exploratory statistical analysis using AIS data and accident reports. *Reliability Engineering & System Safety*. 2018 Aug;176:174–86.

[8] Silveira PAM, Teixeira AP, Soares CG. Use of AIS data to characterise marine traffic patterns and ship collision risk off the coast of Portugal. *The Journal of Navigation*. 2013 Nov;66(6):879–98.

[9] Zhang W, Goerlandt F, Montewka J, Kujala P. A method for detecting possible near miss ship collisions from AIS data. *Ocean Engineering*, 2015 Oct;107:60–69.

[10] Altan YC, Otay EN. Spatial mapping of encounter probability in congested waterways using AIS. *Ocean Engineering*. 2018 Sep;164:263–71.

[11] Yoo SL. Near-miss density map for safe navigation of ships. Ocean Engineering. 2018 Sep;163:15–21.

[12] Benjamin MR, Leonard JJ, Curcio JA, Newman PM. A method for protocol-based collision avoidance between autonomous marine surface craft. *Journal of Field Robotics*. 2006 May;23(5):333–46.

[13] Mou JM, Van Der Tak C, Ligteringen H. Study on collision avoidance in busy waterways by using AIS data. *Ocean Engineering*. 2010 Apr;37(5–6):483–90.

[14] Pietrzykowski Z, Magaj J. Ship domain as a safety criterion in a precautionary area of traffic separation scheme. *TransNav: International Journal on Marine Navigation and Safety of Sea Transportation*. 2017

Mar;11(1):93–8.
[15] Xiao F, Ligteringen H, Van Gulijk C, Ale B. Comparison study on AIS data of ship traffic behavior. *Ocean Engineering*. 2015 Feb;95:84–93.
[16] Ristic B, La Scala BF, Morelande MR, Gordon NJ. Statistical analysis of motion patterns in AIS Data: Anomaly detection and motion prediction. *In FUSION*. 2008 Jun:1–7.
[17] Pallotta G, Vespe M, Bryan K. Vessel pattern knowledge discovery from AIS data: A framework for anomaly detection and route prediction. *Entropy*. 2013 Jun;15(6):2218–45.
[18] Hansen MG, Jensen TK, Lehn-Schiøler T, Melchild K, Rasmussen FM, Ennemark F. Empirical ship domain based on AIS data. *The Journal of Navigation*. 2013 Nov;66(6):931–40.
[19] Harati-Mokhtari A, Wall A, Brooks P, Wang J. Automatic Identification System (AIS): data reliability and human error implications. *The Journal of Navigation*. 2007 Sep;60(3):373–89.
[20] Felski A, Jaskólski K. Information unfitness as a factor constraining Automatic Identification System (AIS) application to anti-collision maneuvering. *Polish Maritime Research*. 2012;19(3):60–64.
[21] Last P, Bahlke C, Hering-Bertram M, Linsen L. Comprehensive analysis of automatic identification system (AIS) data in regard to vessel movement prediction. *The Journal of Navigation*, 2014 Sep;67(5):791–809.
[22] Aarsæther KG, Moan T. Estimating navigation patterns from AIS. *The Journal of Navigation*. 2009 Oct;62(4):587–607.
[23] Nguyen VS, Im NK, Lee SM. The interpolation method for the missing AIS Data of Ship. *Journal of Korean Navigation and Port Research*, 2015 Oct;39(5):377–84.
[24] Shelmerdine RL. Teasing out the detail: How our understanding of marine AIS data can better inform industries, developments, and planning. *Marine Policy*. 2015 Apr;54:17–25.
[25] Eineder M, Suchandt S. Recovering radar shadow to improve interferometric phase unwrapping and DEM reconstruction. IEEE Transactions on Geoscience and Remote Sensing. 2003 Dec;41(12):2959–62.
[26] Prasath VS, Haddad O. Radar shadow detection in synthetic aperture radar images using digital elevation model and projections. *Journal of Applied Remote Sensing*. 2014 May;8(1):1–10.
[27] Banyś P, Noack T, Gewies S. Assessment of AIS vessel position report under the aspect of data reliability. *Annual of Navigation*. 2012;19(1):5–16.
[28] International Telecommunication Union (ITU), 2019. List of Ship Stations and Maritime Mobile Service Identity Assignments: List V. 2001 [cited 2019 Feb 21]. Available from: https://www.itu.int/en/ITU-R/terrestrial/mars/Documents/1st_ListV_compilation%202019.pdf
[29] Yamashita K, Wakabayashi N, Watanabe T. A study of availability and popularisation of class B AIS. *The Journal of Japan Institute of Navigation*. 2012;127:133–40. DOI: https://doi.org/10.9749/jin.127.133
[30] Liu L, Liu X, Chu X, Li J, Jiang Z, He W. Coverage effectiveness analysis of AIS base station: a case study in Yangtze River. In *2017 4th International Conference on Transportation Information and Safety (ICTIS)*. 2017 Aug:178–83
[31] Eilers PH, Goeman JJ. Enhancing scatterplots with smoothed densities. *Bioinformatics*. 2004 Jan;20(5):623–28.
[32] International Telecommunication Union (ITU). Technical Characteristics for a Universal Shipborne Automatic Identification System Using Time Division Multiple Access in the VHF Maritime Mobile Band. 2001 [cited 2019 Feb 21]. Available from: https://www.itu.int/dms_pubrec/itu-r/rec/m/R-REC-M.1371-1-200108-S!!PDF-E.pdf