Towards intelligent navigation in future autonomous surface vessels: developments, challenges and strategies

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Synopsis

There is an increasing trend in developing autonomous surface vessels (ASVs) for a range of maritime activities including transportation, search and rescue and naval operations. Autonomy potentially offers economic benefits, reduced cost, increased operation efficiency and reduced risk. Autonomy means less reliance on human operators, replaced with intelligent decision-making systems. Currently, such intelligence is achieved using sophisticated autonomous navigation systems which may be considered as consisting of three core modules; namely the sensor and data acquisition system, the intelligent planning system, and the automatic control (auto-pilot) system. This paper discusses the state-of-the-art development with a particular interest in reliable and accurate environment awareness. Advantages of using key technologies such as filtering algorithms, fuzzy-logic and statistical learning in autonomous navigation for ASVs have been demonstrated and discussed. Future work also reflects intriguing insights in employing heterogenous sensory modules including LiDAR, radar and vision systems in next generation maritime autonomous navigation.

Keywords: autonomous surface vessels (ASVs); environment awareness; advance sensing technologies; heterogenous sensory systems

1. Introduction:

The maritime industry is advancing with a rapid development of autonomous surface vehicles (ASVs). These can well benefit both civilian applications and military operations. With a reduced need to deploy human operators on-board, ASVs offer the advantages of reduced or elimination of risks to human crew, reduced power consumption and lower manufacturing and operating costs. As such, ASVs exhibit superior performance compared to equivalent sized manned vessels in various marine surveillance missions, such as marine monitoring and surveying, marine waste detection, mapping bridges and waterside buildings and mining. Furthermore, ASVs also play a crucial role in military applications such as anti-terrorism operations, force protection, and electronic warfare.

An increasing research interest in further development of ASVs has been witnessed worldwide, driven by their capabilities to perform a large range of missions. A variety of remotely controlled ASVs have been constructed and are in service, such as the *CEE-ASV* developed by CEE HydroSystems which is used to conduct mine tailings and bathymetry surveys in Arizona, USA. In the meantime, the research into ASVs for autonomous operations is still undergoing active development where the key challenge resides in developing an autonomous navigation system for ASVs. As shown in Figure 1, an autonomous navigation system, also refers to as the Navigation Guidance and Control (NGC) system, is composed of three modules: a data acquisition module (Navigation), a path planning module (Guidance), and an advanced control module (Control). First, the data acquisition module acquires information pertaining to the ASV's own position, speed and heading (obtained using various navigation sensor). It also constructs the surrounding operational environment by detecting target ships (TSs). Based on this information, the path planning module is then tasked to generate a safe path, usually with a series of waypoints, for the ASV to navigate. Finally, the advanced control module will use the generated waypoints as reference points to guide the ASV and ensure that the ASV adheres to the path by controlling its propulsion and steering system.

The implementation of autonomous navigation systems in both civil and military vessels has attracted an increasing attention in recent years with promising solutions proposed for accurate data acquisition. These include using multiple sensors (visual systems, radar and etc) to generate a holistic environment perception system. However, most of these work focus on simple data fusion without a detailed investigation into the capability in dealing with target ships detection subject to complex motions. Also, currently available commercial platforms are mostly suitable for larger-scale vessels with limited understanding in small and light-weight ASVs, which can also be constrained by its payload capacity.

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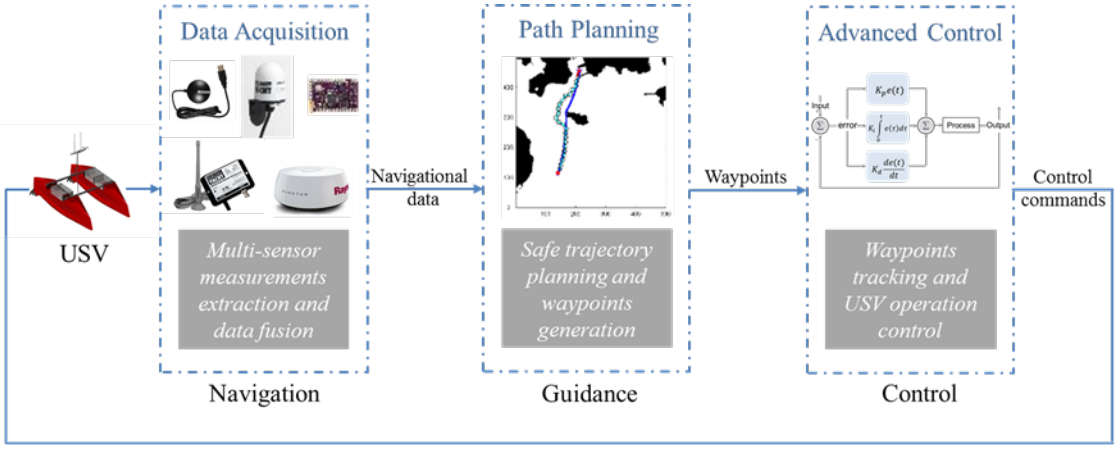

Figure 1 Autonomous navigation system (NGC system) of an Autonomous Surface Vehicle

Contemporarily, the most widely used navigation method is the Global Navigation Satellite System (GNSS), which is able to provide absolute positional information in open area. However, it suffers from problems of signal reliability and continuity in harsh environments. If the GNSS fails the consequences for an autonomous ASV could be disastrous. The ship will have limited certainty as to its current position and other navigational instruments based on it will have their functionality degraded. Therefore, instead of relying solely on the satellite navigation system, the recent trend is to acquire continuous and precise navigational data by interfacing a deadreckoning (DR) system and using the multi-sensor data fusion (MSDF) techniques (Appriou, 2014). For the safe navigation of an ASV, understanding its interaction with the environment is vital. The ASV's NGC system should have the knowledge of static obstacles (e.g. land masses, etc.), the impact off changes in weather, tides, as well as the changing dynamic situation of other vessels (which is referred to as target ships (TS)). Nowadays, existing nautical charts in the market can provide accurate positions of static obstacles and the environmental influences can be determined and accessed by online data. Therefore, the detection of neighbouring moving TSs becomes one of the salient issues that needs to be addressed in the navigation system. The Automatic Identification System (AIS) and marine radar are commonly used to determine positions of dynamic obstacles such as TSs. Marine radar is considered a primary perception sensor system that provides distances from and bearings to TSs, while AIS is a relatively new technology that could obtain the absolute position and course information of TSs from their on-board navigational sensors.

As mentioned earlier, the data acquisition module utilises multiple sensors on-board to process a range of measurements and obtain the information required for the ASV's safe navigation. With a variety of sensors on-board, the research challenge is how to analyse their outputs and develop suitable data fusion algorithms to combine those data streams in an efficient and predictable manner to increase the system measurement accuracy. Ideally, the fusion results would allow the ASV to identify and locate itself precisely and perceive the surrounding environment. However, due to equipment limitations and environmental influences, such as signal loss, unpredictable sensor failure and inaccurate measurements makes this a difficult goal to realise. This work will therefore detail the development of the sensor data acquisition system that can be used in future intelligent autonomous navigation for ASVs. Key points that have been considered in this paper include:

- Introducing a new interacting multi-model (IMM) based target detection in open sea areas using AIS data;
- Proposing a novel multi-sensor data fusion structure for reliable environment perception in constrained areas with limited and unstable access to AIS;
- Providing instructive guidance on next generation heterogenous sensory modules for future autonomous navigation as well as the potential challenges.

2. AIS aided target detection and prediction for ASVs

2.1. *Preliminary backgrounds in using AIS for target ship detection*

In order to increase the degree of autonomy and better ensure navigation safety, ASVs should not only be able to acquire their own accurate and reliable navigational data, but to perceive the surrounding environment to avoid collision risks. Normally, static obstacles, such as small islands and coastlines, can be determined from commercial nautical charts with sufficient accuracy. Detecting dynamic obstacles, such as moving target ships (TS), is a more dynamic challenge. Automatic Identification System (AIS) can provide reasonably accurate

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navigational data of TSs, and a simple AIS receiver can be powered at similar low voltage levels that are also adequate for the navigation sensor system of an autonomous ASV.

The Automatic Identification System (AIS) is an automatic tracking system that is employed by both mariners and the vessel traffic services (VTS) for identifying and locating surrounding vessels to improve maritime safety and developed over the last few decades. AIS messages contain the target ship's dynamic navigational data. AIS data is reasonable accurate as it transmits absolute navigational information of the target obtained from its on-board navigational sensors such as the GPS and electronic compass. As marine electronic devices, common AIS transponders support the NMEA 0183 output format standard, but unlike the GPS or electronic compass that provide measurements in human readable ASCII characters, the AIS messages use 6-bit binary encoding for the bulk of the sentences. The messages commonly contain static information, dynamic information, voyage related information and short safety information. Static information, such as the ship's call sign, name and its Maritime Mobile Service Identity (MMSI) is permanently stored in the on-board AIS transponder. Dynamic information that contains the ship's absolute position, speed and course, is collected from the target ship's own navigational sensors, e.g. GPS receivers, electronic compasses, etc. Voyage related information that includes ship's destination, hazardous cargo type, etc. is set up at the beginning of the voyage. The AIS transponder autonomously transmits messages at different update rates depending on message type which are listed in Table 1. The speed and course alteration will cause different reporting intervals of the dynamic information; the more significant the change is, the faster the message transmits. The information updating interval can be as short as 2 seconds when a high-speed ship is changing its course, while a three-minute interval would be generated for the ship at anchor.

Table 1 Reporting intervals of AIS dynamic messages (1 knot ≈ 0.51444 m/s)

Ship Status	Reporting Interval (s)
Anchored	180
Speed at 0-14 knots	10
Speed at 0-14 knots & altering	4
Speed at 14-23 knots	6
Speed at 14-23 knots & altering	2
Speed > 23 knots	2
Speed > 23 knots & altering	2

Detecting and predicting the navigational data of target ships that are equipped with AIS is a complex process. One of the most effective solutions is to use filtering algorithms such as Kalman filtering (KF) to have an improved capability in acquiring accurate navigational information. With a communal understanding that a vessel over the sea is not designed for both rapid and precise manoeuvring, a constant velocity (CV) model can be used to describe the state of the target ships and consequently integrated into KF.

2.2. *Interacting multi-model (IMM) based target detection*

However, in practical applications, although a vessel conducts the mission to adhere to a straight-line trajectory at a constant speed, the influences caused by water currents and winds would alter its trajectory. The vessel normally makes manoeuvres to correct its course to its destination or the next waypoint. Thus, the adoption of sole CV model is inaccurate and would generate inaccurate predictions when the target is manoeuvring. Therefore, multiple models should be integrated into the system to describe the target's motions more veraciously to provide more accurate detection and prediction results.

2.2.1. Constructing an IMM based Kalman filtering algorithm

Interacting multi-model (IMM) filtering has been widely used in manoeuvring target detection (Kim and Hong, 2004; Wolejsza, 2012; Zhu et al, 2016; Sanchez-Ramirez et al, 2019) since it was first proposed by Blom (1984). According to the International Maritime Organization (IMO), 2002, vessels maintain as steady as possible while operating over the sea. Turning at constant angular velocity is a common manoeuvre of vessels.

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Therefore, a coordinate turn (CT) model is normally used to model the target's manoeuvre (Sanchez-Ramirez et al, 2019).

The state of the target ship can be predicted if the angular velocity is known. However, AIS cannot provide the measurement of the target's angular velocity. Therefore, the angular velocity should be considered as a parameter rather than a variable to generate multiple models and an interacting multiple model estimator has been integrated to the KF based target detection and prediction algorithm to model the target's manoeuvres.

The Interacting Multiple Model Kalman Filter (IMMKF) has been proposed to calculate the possibilities of each of the predefined models and generate the fused navigational data accordingly. Figure 2 illustrates the designed IMM-filter for the CV model and the CT model combined ship motion model. Suppose the CV model and the CT model are denoted as Model 1 and Model 2. For one operation cycle (at time step *k*), the IMM-filter first calculates the mixing probability of the two models based upon the probability of each model as calculated in the previous time step. The mixed inputs for CV model based KF and CT model based KF can then be calculated by referring to the mixing probability. By using the measurement *Z(k)* and the calculated mixed inputs, ship's state and covariance are updated using two Kalman Filters together with the likelihood of the measurement of each filter. The likelihood of each filter can be interpreted as the confidence level of current filter, i.e. small measurement residual will produce a high likelihood of the current filter meaning the filter is more accurate and should be more relied upon at that moment.

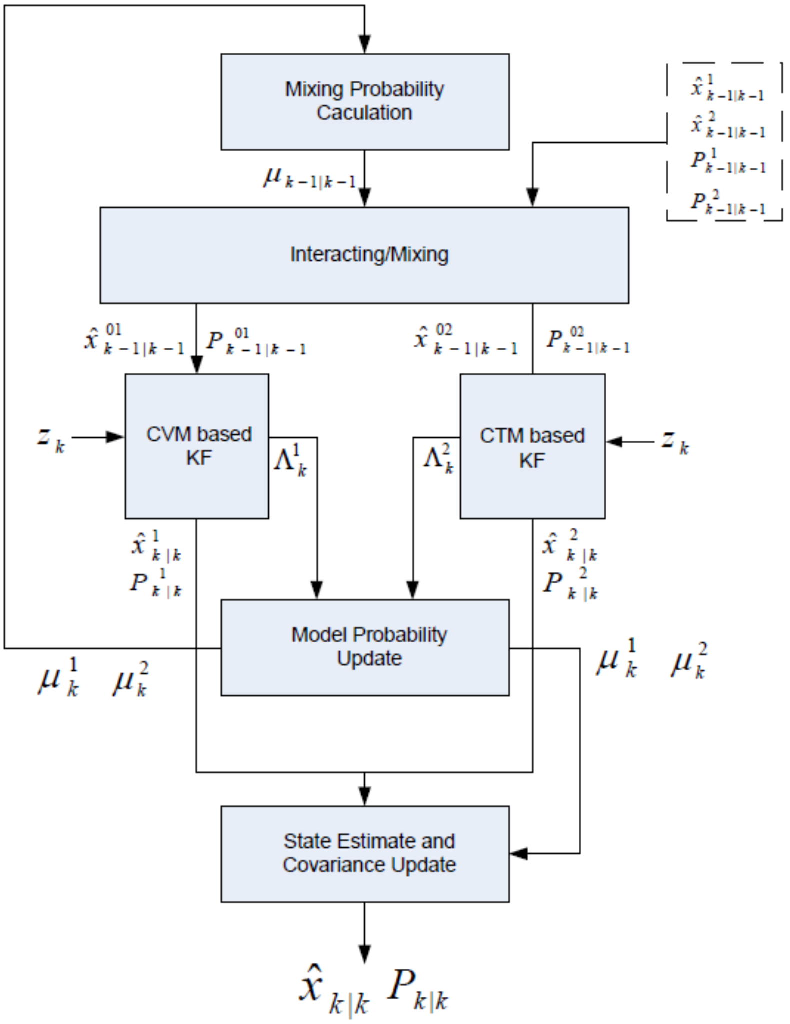

Figure 2. Working mechanism model for Interacting Multiple Model Kalman Filter.

2.2.2. Multi-factor manoeuvre detector

The computational cost of multiple models becomes quite high with the increasing number of the models, which introduces a degree of non-practicability to real-time systems. Manoeuvres represent a change in the target motion pattern therefore detecting the manoeuvre of the target first offer a solution to reduce such

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computational cost since the multiple model-based data fusion algorithm will only be employed when manoeuvring of the target is detected. Chi-square based detectors are widely used in manoeuvring target detection (Li and Jilkov, 2002). For an n dimensional Gaussian distributed vector $x \sim \mathcal{N}(\hat{\boldsymbol{x}}, P)$, its covariance is Chi-square distributed. Therefore, the proposed detector employs the covariance of system residuals in the proposed IMMKF target detection and prediction algorithm to compare with the Chi-square defined thresholds (Equations (1) and (2)). The thresholds are listed in Table 2, where α is the probability and $1 - \alpha$ is the level of confidence, which is typically set at 95% or 99.5% by the system. The detector identifies whether the target is making manoeuvres by Equation (3). This procedure will save a significant amount of the computational cost generated by the multiple model filter.

$$\boldsymbol{\varepsilon}(k) = \boldsymbol{z}(k) - \boldsymbol{H}\hat{\boldsymbol{x}}(k) \tag{1}$$

$$dc(k) = \left|\boldsymbol{cov}\left(\boldsymbol{\varepsilon}(k)\right)\right| = \boldsymbol{\varepsilon}'(k)\,\boldsymbol{S}_T(k)^{-1}\boldsymbol{\varepsilon}(k) \tag{2}$$

$$dc(k) > \eta = {\chi_n}^2(\alpha) \tag{3}$$

Table 7. 2 Chi square distribution ${\chi_n}^2$

Confidence $(\mathbf{1} - \boldsymbol{\alpha})$	**95%**	**99%**
Probability level $(\boldsymbol{\alpha})$	3.84	0.01
$\boldsymbol{\eta^2}$ $(\boldsymbol{dof} = \mathbf{2})$	5.99	9.21
$\boldsymbol{\eta^2}$ $(\boldsymbol{dof} = \mathbf{3})$	7.81	11.345
$\boldsymbol{\eta^2}$ $(\boldsymbol{dof} = \mathbf{4})$	9.49	13.277
$\boldsymbol{\eta^2}$ $(\boldsymbol{dof} = \mathbf{5})$	11.07	15.086

Once the target is detected as manoeuvring, the above interacting multiple model algorithm is applied to determine the system states.

2.3. Case studies of the AIS aided target detection and prediction algorithm

In this section, AIS measurements are simulated to determine a single dynamic target's navigational data as well as to make predictions during the long AIS data-transmitting intervals. The target ship is treated as a single point without considering its actual size. Portsmouth Harbour (Figure 3(a)) is used to simulate a practical environment for the target. It has first been converted into a binary map (Figure 3(b)), which has the dimension of 800 pixels * 800 pixels representing a 1.2 km * 1.2 km area (1 pixels =1.5 m). The simulated target is assumed to be operating at constant and initially adheres to a straight line trajectory. Additionally a current vector with the speed of 0.3 m/s at 155° is simulated that has the effects of pushing the target towards the southeast. The trajectory of the target is therefore altered and the target has a constant angular velocity of 3 °/s when manoeuvring to correct its course, which is presented in Figure 3(b). The initial speed of the target is 7 knots on a course of 160°, while the updating intervals of the AIS measurements are 10 seconds under normal condition and 2 s when manoeuvring. The tracking start point is (450 m, 1200 m) and the end tracking point is (850 m, 64 m). The sampling time between each time step is 2 s. The target starts to manoeuvre after time step k=140. Eight angular velocities from -4 °/s to 4 °/s that cover most frequently used angular velocities of a vessel are chosen to generate 8 models.

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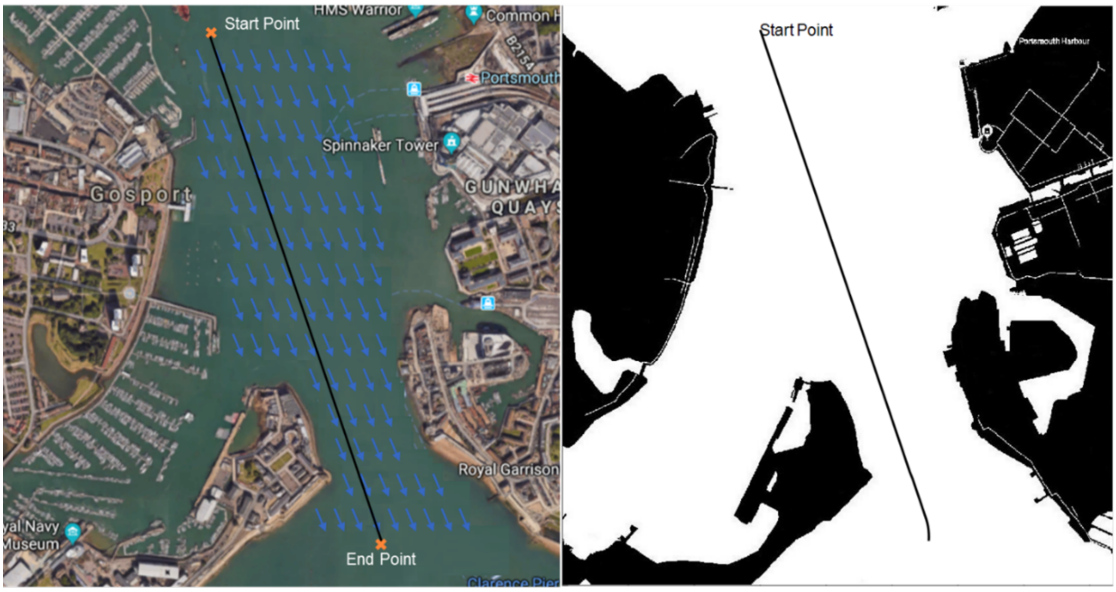
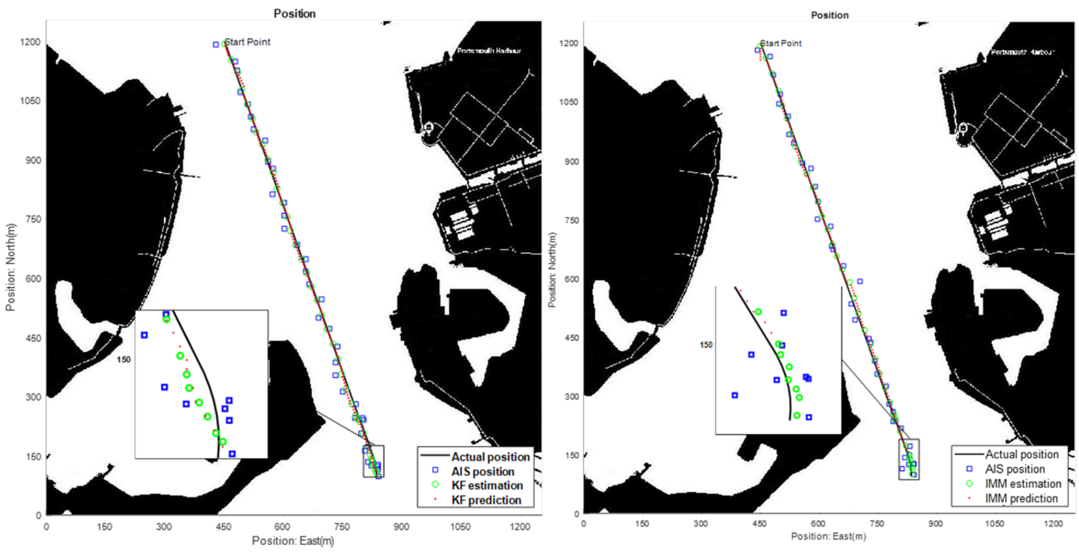


(a) (b)

Figure 3. Simulation scenario: (a) testing environment in Portsmouth harbour with a constant current and the simulated straight trajectory of the target; (b) the binary map and the altered true trajectory of the target

Figure 4(a) demonstrates the simulation results with an enlarged inset detailing the end of the trajectory, where the target is conducting manoeuvres. It can be seen that the AIS data (blue squares) are updated more frequently when the target is approaching the end of its trajectory since it is correcting its course to get to its end point. However, the estimated positions (green circles) of the target are driven to an incorrect direction when the target is manoeuvring. The simulation results confirm the effectiveness of the constant velocity model based conventional KF target detection and prediction algorithm when the target is not manoeuvring, but it is incapable of estimating the correct course of the target during manoeuvring although the AIS data updates more frequently. Figure 4(b) demonstrates the simulation results of the proposed IMMKF AIS aided manoeuvring target detection and prediction algorithm. The manoeuvring target detection algorithm performs better at estimating the positions and courses of the detected target. It can be seen from the enlarged inset of Figure 4(b) that the estimated positions (green circles) adhere to the true trajectory (black line) while the target is manoeuvring.



(a) (b)

Figure 4. The simulated AIS measured positions and the predicted and estimated position results using (a) standard KF and (b) IMMKF algorithms.

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The probability of each model shown in Figure 5 expresses how the proposed IMMKF based algorithm determines which model is the correct. Before time step k=140 when the target is not manoeuvring, all the probabilities of the 8 models (mu1, mu2, mu3, mu4, mu5, mu6, mu7 and mu8) remains at 0. It can be seen that at the beginning of the manoeuvring period, the probabilities of mu3, mu4 and mu6 are peaked and return to 0 in a short time. It is caused by the insufficient data obtained by the manoeuvre detector algorithm at initial stage. After extracting enough data, the proposed algorithm determines the correct model mu7 that represents the angular velocity of 3 °/s and its probability becomes the largest and tends to 1 during the target's manoeuvring, which is the same as the target's actual angular velocity. The results prove the effectiveness of the designed manoeuvre detector.

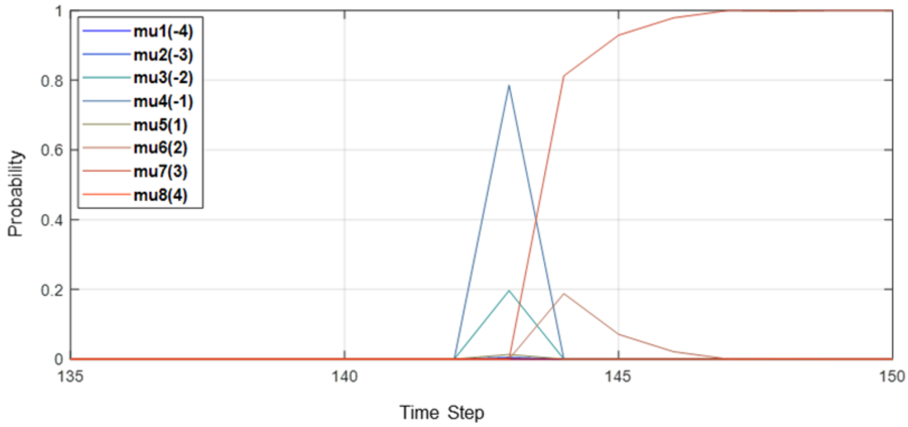

Figure 5. The probabilities of each manoeuvring model generated by the IMM filter.

3. Fuzzy logic based multi-sensor data fusion for reliable autonomous navigation

Although, an increasing number of vessels are installing AIS devices, only large ships over 300 gross tonnage are required to install transponders (Maritime & Coastguard Agency, 2007; Lloyd's list intelligence, 2017). Small vessels are normally equipped with AIS receivers, so that they would only be aware of other target ship's information instead of sending their own information at the same time. In addition, AIS is broadcast on VHF radio waves that travel in straight lines. When an ASV encounters a complex environment surrounded by multiple target ships, especially in harbour, AIS data is prone to be lost due to the electromagnetic influence. The location of AIS transceivers or the types of the AIS transceivers and weather conditions could also affect the quality of the AIS signal. As a consequence, relying solely on AIS to detect targets is unlikely to prove satisfactory for autonomous ASV navigation. Marine radar has been regarded as a prime solution to perceive the surrounding environment in maritime vessel navigation for many decades. It measures the relative distance and bearing by calculating the transmission time of the echo of an electromagnetic wave pulse. This feature of a marine radar could enable the ASV to detect all the targets surrounding the ASV within radar detection range, which is typically 48 nautical miles, but associated with a large degree of uncertainty. The target detection can be difficult while using either the AIS or the marine radar alone in harsh environments with an unknown number of targets that varies with time. To improve system reliability, both sensors are employed as complementary devices to perceive the surrounding dynamic environment. A fusion algorithm is therefore required to merge the measurements from the two different sources.

Most of the current studies on Radar and AIS data fusion are concerned with synchronising, associating and fusing the different measurements from each sensor (Habtemariam et al, 2014; Pelich et al, 2015;). In this research, raw radar and AIS measurements will not be associated and fused directly. They will be associated with each detected target track individually. The system states are then updated by the proposed manoeuvring target detection and prediction algorithm from section 2 using the associated sensor measurements respectively, and the final fusion algorithm generates the estimated target's navigational data by fusing the updated estimations. The system structure is demonstrated in Figure 6.

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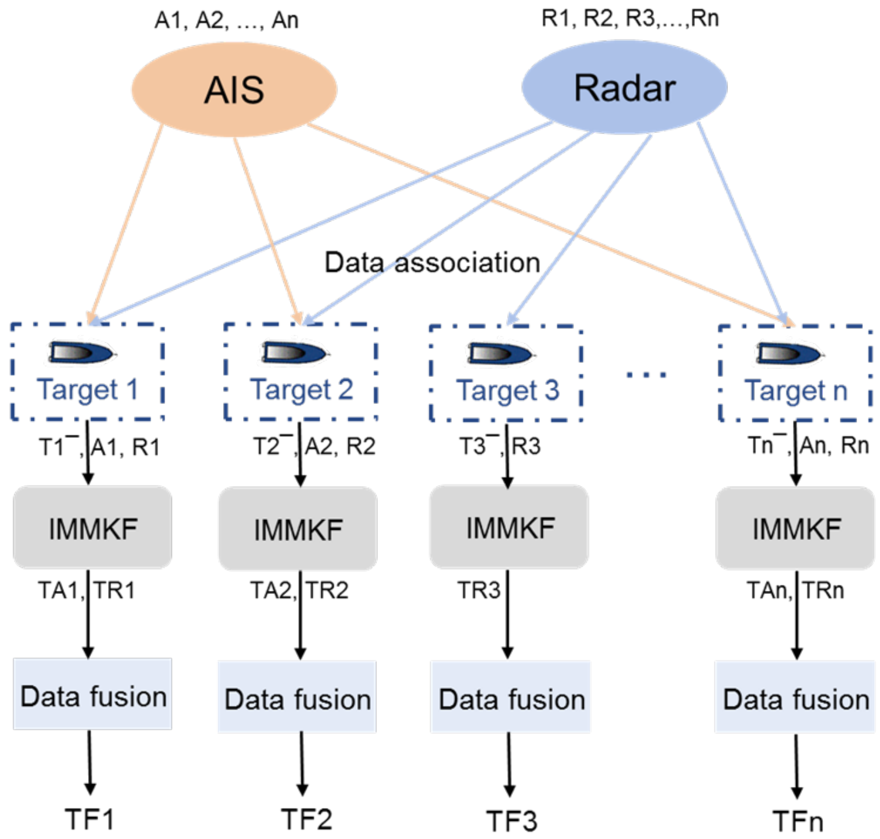

Figure 6. System structure of multi-target detection using AIS and radar measurements.

4. Trends and challenges in future heterogenous multi-sensor suites

Although Radar can detect TSs over a wide range of areas with a reasonable performance, the radar scatters may provide false sizes of TSs due to reflection or disturbance. Moreover, the sampling rate and resolution of Radar are relatively low compare to other sensors, such as LiDAR and vision sensors. Therefore, to enhance the awareness capabilities of ASV, especially for detecting high-speed TS or small size obstacles, additional sensors are necessary to be integrated into the sensing system on board.

4.1. Multi-sensor suite

Figure 7 shows representative sensors used in a typical multi-sensor suite for ASV, including visible band sensors such as electro-optical camera, infrared band camera (IR camera), LiDAR (near infrared band), frequency modulated continuous wave (FMCW) Radar, IMU, AIS and GPS/GNSS.

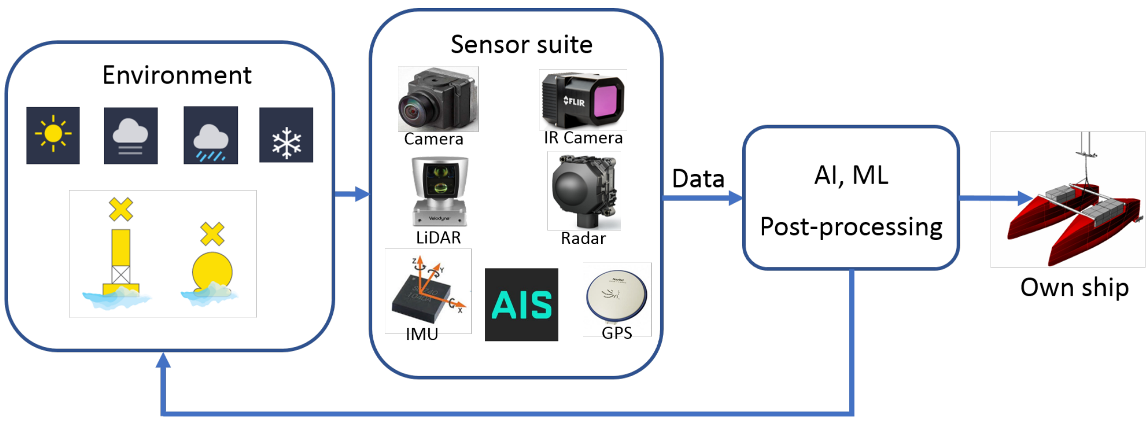

Figure 7. A typical multi-sensor suite on board.

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- ***Camera***: The most common camera system used in ASV is stereo camera system with multiple cameras displaced in a circular to create a 360º of field of view. The processed image results can generate a depth map for obstacle detection and avoidance.
- ***IR camera***: Based on thermal radiation that propagated through atmosphere, the IR camera converts the temperature into thermal intensities and generates thermal images.
- ***LiDAR***: LiDAR measures the time of flight of pulsed lights to create a 3D map of the environment that represented by point clouds.

To acquire more accurate estimation of TS states, such multi-sensor tracking approaches have been introduced in several studies. A tracking filter was designed using multi-radar for maritime surveillance by Nikolio et al, 2016. Radar and Lidar were integrated for tracking of multiple targets by using extended Kalman filter (Han et al, 2017). Zhang et al, 2017 combined the measurements from camera and LiDAR to find the true target detected by Radar. In such a case, the blind zone of Radar can be minimised. Additionally, in AMN project (Elkins et al, 2010), JPL stereo camera were integrated together with LiDAR, radar and AIS for testing cooperative missions over long hours. Sorbara et al, 2015 improved the capability of obstacle detection at night by integrating the LiDAR with IR camera. However, most of studies do not generally consider the influence of weather on the sensors used on ASVs. As in human vision, these sensors are negatively impacted by adverse weather conditions. For example, the functions of camera and LiDAR drop off significantly with reduced operating range and signal contrast in rainy and foggy conditions (Liu et al, 2016).

4.2. *Challenges and solutions*

4.2.1. *Weather influences*

The influence of weather on sensors can be summarized as shown in Figure 8. It can be seen that image sensors such as camera and IR camera, and LiDAR are most prone to be influenced by severe weather conditions, while Radar has a relative steady performance.

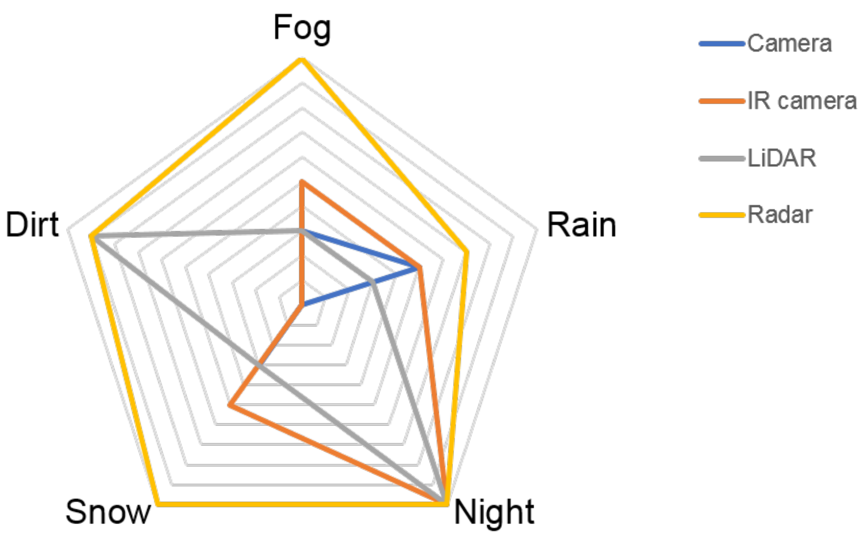

Figure 8. Weaknesses of sensors on board in different weather conditions.

Because of the special operating environment of ASV. It is difficult for ASV to survive under changeable weather. Therefore, it is important to investigate how the adverse weather will further influence the detection and tracking of obstacles. Due to high cost of sensors used in ASV, the most common method is to test sensors performances in simulations. Traditionally, historical sensor data collected in real world can be imported into simulations and using the data to train ASVs. Whereas, more advanced simulation tools would be able to integrate with nautical chart and sensor models to create a simulated operating environment. To achieve a realistic simulation, the environment needs to:

- Simulate dynamic artefacts including different weather conditions and physical dirt that may degrade sensor performances.
- All sensors must be simulated based on physical models in order to verify the robustness of tracking algorithms. For example, LiDAR needs to be simulated and operated at a high frequency

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and high level of fidelity. In such a way, a virtual world can be constructed, and potential problems can be identified.

4.2.2. Hardware limitations

Hardware limitations of sensors can also lead problems to sensing performances. Long-time exposed under sun and water may cause corrosion or damage to sensors. Also, when ASV operating on surface of water, sensors on board cannot be fixed at one point to undertake measurements. Sensors like LiDAR that requires static scanning can generate incorrect object detection. As the instantaneous coordinates are different while moving, the generated point cloud may not contain any shape information. To solve these problems, several techniques can be made:

- Data fusion techniques. For example, combine LiDAR with IMU and GPS sensors for motion corrections, and apply multiple and overlapping sensors.
- Image post-processing. Advanced image processing techniques are required in order to reduce background noises, especially for IR images that have false colour.
- Artificial Intelligent (AI) algorithms. Deep-learning techniques, such as faster regions with convolutional neural network (R-CNN) features can be used to enhance the performance of vision-based detection. However, all AI algorithms are subject to training data sufficiency and the training process should be well designed to avoid problems such as over-fitting.

5. Conclusions

In this paper, recent advances in reliable situation awareness for ASVs have been introduced and discusses. Based upon specific sensory suites (AIS equipped or AIS/radar equipped), different data processing and fusion algorithms have been designed to achieve an accurate perception of moving ships. Such an environment perception capability can be integrated with other key functionalities such as planning and control to support an efficient fully autonomous mission. Challenges generated from uncertain environmental aspects have also been discussed in this paper. New heterogenous sensory modules such as computer vision/LiDAR systems are proposed as one of promising solutions for future ASV autonomous navigation.

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