The design of an autonomous maritime navigation system for unmanned surface vehicles

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Abstract

This paper presents the development of an autonomous maritime navigation system for unmanned surface vehicles (USVs). In the autonomous system various maritime navigational devices are connected to obtain necessary navigational information but with uncertainties. To improve signal accuracy as well as robustness, a novel multi-sensor data fusion algorithm is proposed and developed. Then, a new predictive path planning algorithm is employed to provide an advisory collision-free trajectory. Practical trials and computer based simulations are carried out to prove the effectiveness of the developed system.

1. Introduction

Unmanned surface vessels (USVs) are currently under development to benefit military operations, to provide maritime policing and a new means of cost effective cargo transport. Key to USVs is the development of a marine autonomous navigation system which is one of the essential elements to ensure safe operation for ocean and coastal navigation, and when berthing. An autonomous marine navigation system requires accurate position and attitude of Own Ship (OS), mapping of the environment including static and dynamic obstacles, a path planning capability and a collision avoidance system. Fig.1 illustrates a proposed autonomous navigation system structure with two different modules to meet such requirements.

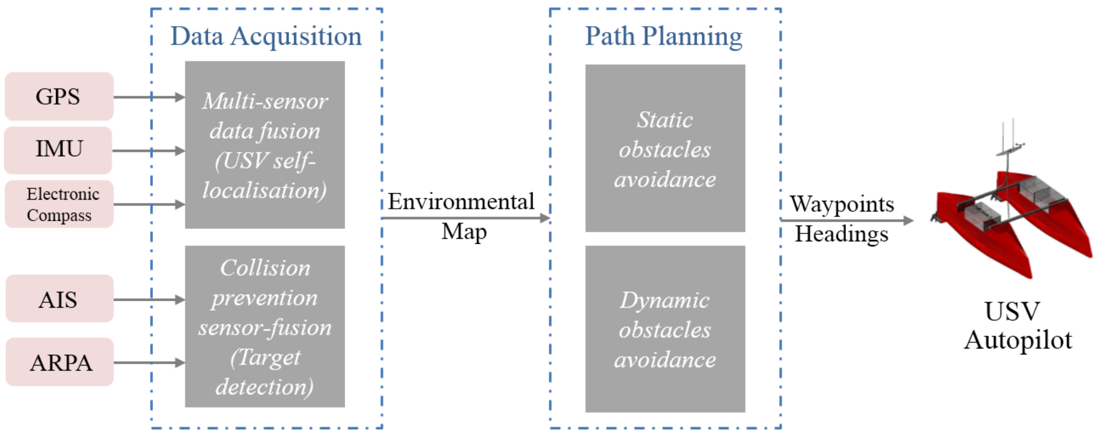

Fig. 1 System structure for an autonomous navigation system

The data acquisition module acquires information about the own USV's position, speed, attitude etc. using various sensors such as Global Positioning System (GPS) receivers, inertial sensors for dead reckoning (DR) and electronic compasses. This module is also required to perceive the surrounding environment and obtains moving obstacle positions from the Automatic Identification System (AIS) and marine radar. A large amount of sensor data is obtained by the data acquisition module so proper data merging and fusion must occur before generating a synthetic picture or map of the surrounding field. Based upon the map built up by the data acquisition module, the path planning algorithm has the responsibility to generate a safe path with desired waypoints and requested headings for the autopilot to control the USV so as to avoid both static and dynamic obstacles, e.g. coastline, target ships (TSs).

Multi-sensor data fusion (MSDF) for vehicle's navigation has advanced in recent years; normally a multi-sensor navigation system is hybrid that having both Global Navigation Satellite System (GNSS) and DR system. Most of these integrated systems employ a GPS receiver, several inertial sensors and usually an electronic compass. Some advanced systems would also include sensors like a speed log and perhaps a camera. Caron et al. (2007) proposed particle multi-data sensor fusion algorithms for land vehicle, and concentrated on observing sensors failure and integrated multiple sensors to improve unreliable GPS information. Jared and Gerard (2011) proposed several data fusion algorithms for a GPS receiver and several inertial measurement units (IMUs), which provide good performance when reducing GPS position error. Zhang et al (2005) implement a Kalman Filter to improve the reliability of GPS, IMU and electronic compass measurements. In terms of USV application, Liu et al. (2014) developed a Kalman filter based algorithm to obtain accurate positions, speeds and headings of an USV. However, it should be noted that sensor failure, which is another impact that affects the accuracy of USV's navigational data, hasn't been considered in such applications. If one of the sensors fails the consequences could be disastrous since the USV will lose its current situation. An effective method of detecting and disregarding the failed sensor should be considered.

In this paper, an improved autonomous navigation system concept has been proposed. First, a fuzzy MSDF algorithm is developed for the event of a sensor failure and to provide robust navigational information. Based on obtained information, a new predictive path planning algorithm using the fast marching method (FMM) is designed to specifically address the dynamic path planning problems. Such a system integrates the planning and prediction modules in order to obtain an efficient navigation system. Its capability has been tested using both computer based simulations and a USV platform.

2. Fuzzy multi-sensor data fusion algorithm

The multi-sensors data fusion algorithm is designed to provide robust navigational information for the system. The system employs the Federated Filter Architecture, which was first proposed by Carlson (1988). It is a two-stage filter architecture, each sensor is fused with the reference sensor and constitutes a final optimal estimation by a master filter or a sensor management process.

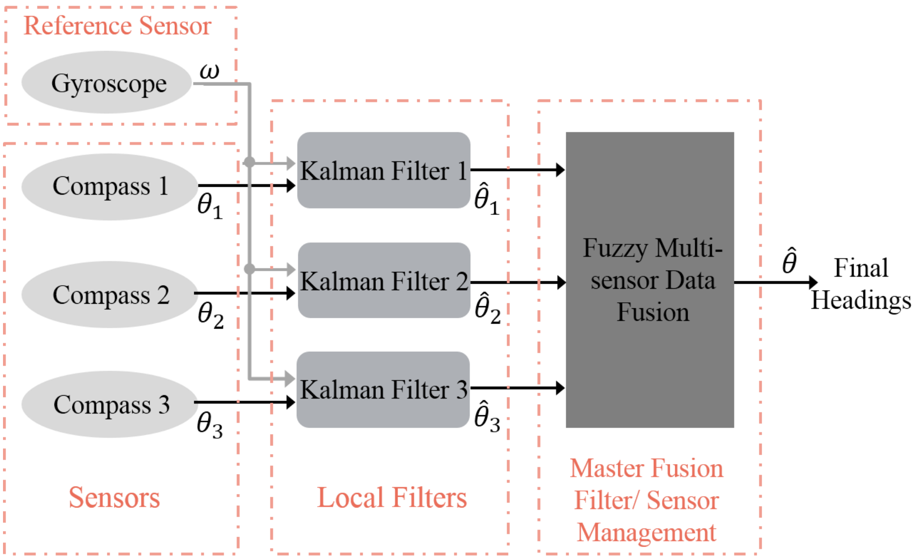

Fig. 2 Federated Filter Architecture for the Fuzzy MSDF Algorithm

Compared to a land vehicle, ships at sea are normally operated at a constant speed and headings changes are the primary means of collision avoidance. Therefore the MSDF algorithm is dependant upon monitoring the correct working of electronic compasses. As Fig. 2 demonstrates, three independent electronic compasses represent local sensors to provide absolute headings of the USV; and a gyroscope is used as the reference for USV's rotation rates. These sensors feed to the local filter which employs the Kalman filter as implemented by Liu et al. (2014). A fuzzy system acts as a master fusion process to cope with possible sensor failures by assigning a weight to each of the local KF state estimates.

2.1. Fuzzy input and output sets

The inputs of the fuzzy system are from the local Kalman filters and the outputs are different weights for each KF estimates, as illustrated in Fig.3.

Fig. 3 Fuzzy system (input and output sets)

The master fused state estimate is then computed by the weights as:

$$\hat{x}(k) = \sum_{i=1}^{3} w_i(k)\, \hat{x}_{KF_i}(k) \tag{1}$$

The weightings are determined by observations of the innovations sequence of each KF, where the innovations sequence of a KF is defined as:

$$inn(k) = z(k) - H\, \hat{x}(k) \tag{2}$$

i.e. the difference between the compass measurement and the predicted heading angle at each time-step k. Under an ideal scenario, the innovations sequence should be comprised of a zero-mean, white noise sequence (Subramanian et al, 2009, Bijker et al, 2008). This sequence could be monitored to detect a failure in the correct estimation by one of the KFs and to monitor the innovations sequence, which in general is a random process where the individual value is meaningless, a simple moving average (SMA) of the innovations sequence of each KF is computed:

$$SMA(k) = \frac{inn(k) + inn(k-1) + \cdots + inn(k-K+1)}{K} \tag{3}$$

where K is the number of samples considered in the moving average. Since the SMA is, in the ideal case, a sum of zero-mean independent random variables, it is in itself a zero-mean random variable, and tends to be normally distributed by the Central Limit Theorem. However, its variance is K times smaller than that of the innovations random variable. Thus, sporadic high values of the SMA are more improbable than for the innovations, and will almost only occur when the innovations stops being a white sequence. Hence it is chosen to indicate a compass fault in the KF estimate.

2.2. Membership functions and if-then rules

In order to obtain a smooth decision process, the following fuzzy membership functions are defined:

Negative function: $$\mu_N = \begin{cases} 1 & if\ SMA < SMAN \\ SMA/SMAN & if\ SMAN \le SMA < 0 \\ 0 & if\ SMA \ge 0 \end{cases} \tag{4}$$

Zero function: $$\mu_z = \begin{cases} 1 - SMA/SMAN & if\ SMAN \le SMA < 0 \\ 1 - SMA/SMAP & if\ 0 \le SMA \le SMAP \end{cases} \tag{5}$$

$$\text{Positive function: } \mu_P = \begin{cases} 0 & if\ SMA\ <\ 0 \\ SMA/SMAP & if\ 0\ \leq\ SMA < SMAP \\ 1 & if\ SMA\ \geq SMAP \end{cases} \tag{6}$$

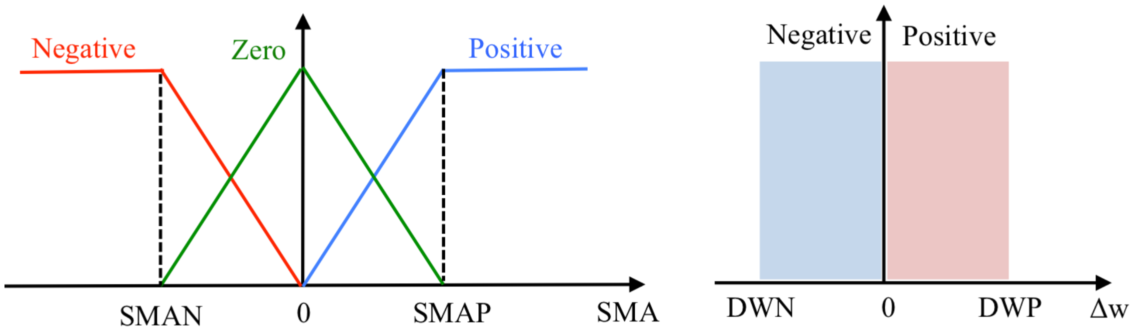

Fig. 4 Input & output membership functions

As indicated by the output fuzzy membership functions (Fig. 4), the output to the fuzzy logic inference system is chosen to be a change in the weight of the filter, Δw, rather than the weight itself. This is to avoid brusque transitions in the overall estimate. The following fuzzy rules can now be established:

Rule 1: If SMA negative then Δw is negative
Rule 2: If SMA is zero then Δw is positive
Rule 3: If SMA is positive then Δw is negative

2.3. Defuzzification

Then, at each sampling time k, depending upon the value of the SMA, Δw is defuzzified by applying Centroid method (Sameena et al., 2011) as follows:

$$\Delta w^* = \frac{\int \mu_i\ \Delta w\ d\Delta w}{\int \mu_i\ d\Delta w} \tag{7}$$

where μ_i represents the membership function (μ_N, μ_Z, or μ_P), Δw^* is the defuzzified output and Δw is the output variable.
Once Δw has been calculated at time step k for each KF ($\Delta w_i(k)$, $i = 1,2,3$), these values are normalised so that their sum equals to zero to ensure that the sum of Δw_i remains one,

$$\Delta w_{i,n}(k) = \Delta w_i(k) - \frac{1}{3}\sum_{j=1}^{3} \Delta w_j(k)\,, \qquad i = 1,2,3 \tag{8}$$

The resultant updated weights of each filter is given by:

$$w_i(k) = w_i(k-1) + \Delta w_{i,n}(k)\,, \qquad i = 1,2,3 \tag{9}$$

The initial weights are assumed to be equal ($w_i = \frac{1}{3}, i = 1,2,3$) and they are not modified until time instant K has been reached, which is the number of samples required to compute the SMA. This novel fuzzy system could also be applied to other applications as long as more sensors could be integrated, e.g. several GPS receivers.

3. Target ships detection

With the knowledge of OS's navigational data and relative detecting sensors, the dynamic target ships surrounding the USV can be detected so as to allow the generation of the safe path. TSs navigational data fusion has analogous process as own USV. But the data are obtained from different sensors, and require different data conversion and decoding process. In this paper, an AIS receiver is simulated to determine surrounding dynamic obstacle positions as well as to predict their positions during the AIS data-transmitting intervals.

3.1. AIS decoding procedure

The AIS is an automatic tracking system that is employed by both mariners and the vessel traffic services (VTS) for identifying and locating surrounding vessels. The AIS data normally provides 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 mounted AIS transponder. Dynamic information that contains the ship's position, speed and course, is collected from the ship's own navigational sensors, e.g. GPS receivers, speed logs and electronic compasses, etc. Voyage related information that includes ship's destination, hazardous cargo type, etc. is set up at the beginning of the voyage (Lin, et al. 2008). Unlike other sensors that provide measurements in human readable ASCII characters, the AIS messages use 6-bit binary encoding for the bulk of the sentences to reduce the amount of data. Fig. 5 indicates the flow of decoding an AIS message. Firstly, the valid characters in the AIS message are analysed and converted to the 6-bit binary to form a long-bit binary sentence. Then the message type can be determined from the first 6-bit and all the binary is further converted to decimal values according to the data position distribution of each message type. Finally, some information like ships name, destination needs to be converted from the decimal values to the corresponding ASCII characters.

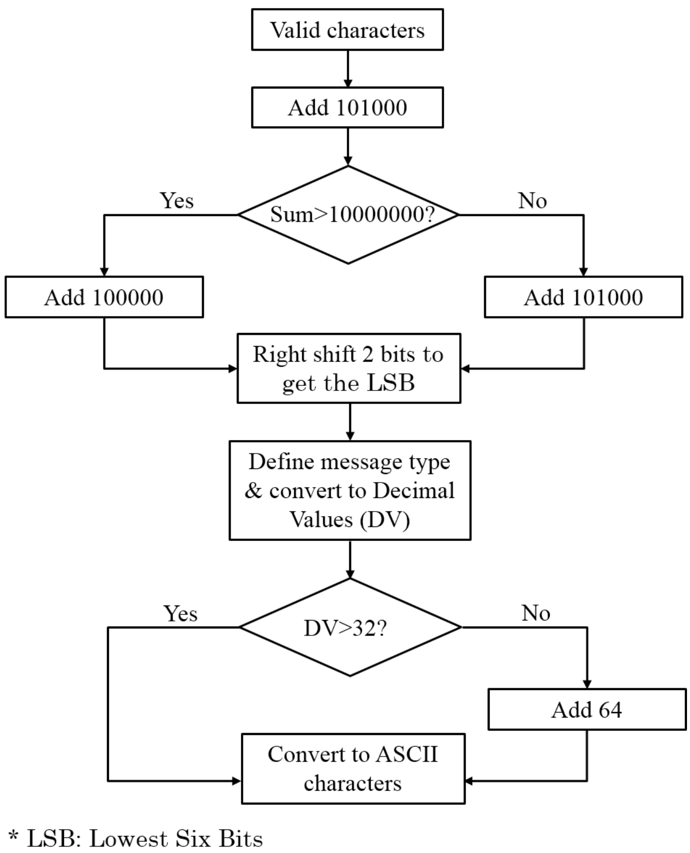

Fig. 5 Flow chart of AIS data decoding

3.2. TSs positions predictions

The AIS transponder autonomously transmits messages at different update rates depending on message types. The speed and course alteration will cause different reporting intervals of the dynamic information; the bigger the change is, the faster the message transmits. The information updating intervals can be as short as 2 seconds for the course change of a high-speed ship, while a 3 minutes interval would be generated for the ship at anchor. Therefore TS positions predictions during the time intervals are valuable for the PPM to take actions of collision avoidance and a KF algorithm is applied to cope with this situation. Assume a TS is operating in a constant speed nearby the USV and may have a collision then the real time positions of this TS is required for the path planning algorithm to generate a safe path to avoid the collision. Hence, the system state vector can be defined as following:

$$x = [p_x \;\; p_y \;\; v_x \;\; v_y]^T \tag{10}$$

where p_x and p_y represent the positions, v_x and v_y are velocities in x and y direction. Then the state model of the TS positions determination can be determined below:

$$x(k) = \begin{bmatrix} 1 & 0 & T_s & 0 \\ 0 & 1 & T_s & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} x(k-1) + \begin{bmatrix} \frac{{T_s}^2}{2} & 0 \\ 0 & \frac{{T_s}^2}{2} \\ T_s & 0 \\ 0 & T_s \end{bmatrix} u(k) + w(k-1) \tag{11}$$

where T_s is the sampling period, w is the random variables that represents AIS measurement noise, and the control input $u(k)$ is defined as:

$$u(k) = [\alpha_x(k)\,, \alpha_y(k)]^T \tag{12}$$

where α_x and α_y are zero-mean white noise in x and y directions to model the uncertain accelerations, which only causes small deviation for the velocities in x or y directions. As aforementioned, the observations are provided by the decoded AIS messages, which give the absolute positions of the detected TS. Therefore, the system measurement model can be determined as:

$$z(k) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} x(k) + v(k) \tag{13}$$

During each AIS information update interval, the KF algorithm only executes the Prediction process shown in Fig. 6 for each sampling time, which generates possible positions of the TS so that the PPM is able to investigate whether the distance between the TS and own USV is in the safe range. This method is highly effective as the time interval will be long only when the movement of the detecting TS is stable. After the updated AIS measurement inputs to the algorithm, the KF will carry out its two-step process and reduces measurement noises to improve AIS data accuracy.

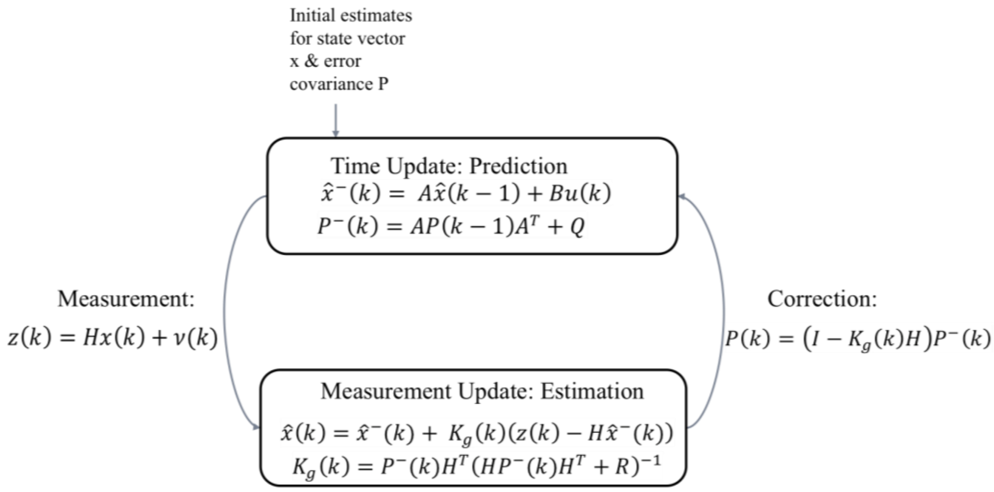

Fig. 6 Kalman Filter Process

4. Path planning algorithm for dynamic obstacles avoidance

This proposed algorithm consists of two functionalities, i.e. the collision risk assessment (CRA) function and the path planning function. It is assumed that the dynamic information of moving ships, such as velocities and instantaneous positions, can be obtained by using on-board sensors or navigation devices. Based on such information, the CRA first employs the Kalman Filter (KF) algorithm to detect and predict the movements of the moving TS in defined time steps, and assesses the collision risks. If it is required to avoid the TS, a safe area around the ship will be generated to improve collision avoidance. When planning the trajectory, a weighted FMS algorithm proposed in Liu et al. (2015) is used.

4.1. Collision risk assessment

Once the path of the moving ship in next time periods have been detected and predicted, to assess the collision risk the trajectory of USV itself should be estimated. Assume that USV is navigating in a 2D space and has access to its own travel information such as current position, velocity, heading angle and turning rate; according to the kinematic equations of USV, the nonlinear estimation model of USV itself is established as:

$$\begin{cases} x(k+1) = x(k) + \Delta t * v(k)\cos\varphi(k) \\ y(k+1) = y(k) + \Delta t * v(k)\sin\varphi(k) \end{cases} \tag{14}$$

$$\varphi(k+1) = \varphi(k) + \Delta t * \alpha(k) \tag{15}$$

where $x(k)$ and $y(k)$ represent the position in x and y directions at time step k, $v(k)$ is the velocity magnitude at time step k with heading angle as $\varphi(k)$ and $\alpha(k)$ is the turning rate. Then, as shown in Fig. 7, based on these two predicted paths, the smallest distance between them can be calculated. If this distance is less than the predefined safety distance two ships will have the possibility of colliding, hence appropriate collision avoidance manoeuvres need to be taken.

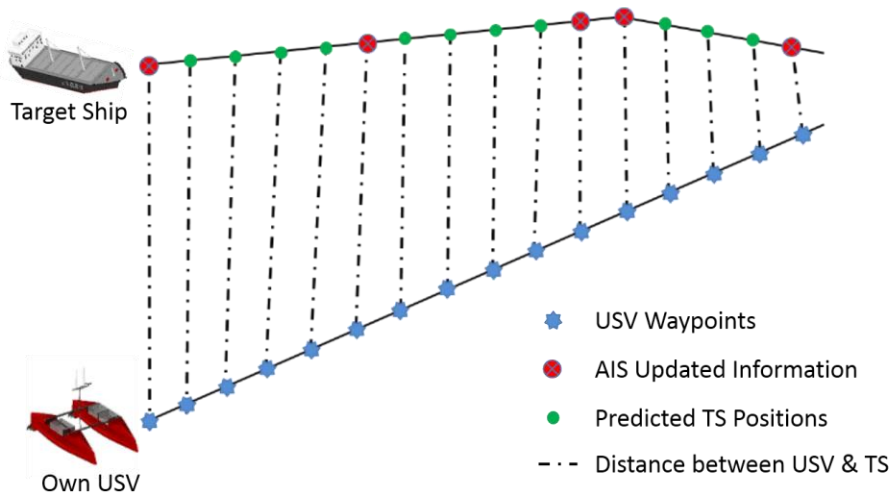

Fig. 7 Collision risk assessment

4.2. Path planning algorithm

Based on the weighted FMS method and the collision risk assessment algorithm, the predictive path planning algorithm for USV can be developed.

Fig. 8 illustrates the flow chart of the path planning algorithm and the details are listed below.

- The algorithm first takes in the navigation map, where static obstacles have been clearly represented and stored as an original binary map $\boldsymbol{W_o}$. Such a map can be obtained through commercial charts, such as marine navigation charts. Also, advanced sensor technology, such as the Simultaneous Localisation and Mapping (SLAM), can be used to construct the map of the unknown environment while the USV is navigating.
- Based on the map received, the safety map $\boldsymbol{W_s}$ will be first generated and combined with $\boldsymbol{W_o}$ to have an initial map $\boldsymbol{W_{ini}}$. A collision free path $\boldsymbol{\tau_{ini}}$ in such environment will be sought by using the FMM and stored as the guidance route. By following $\boldsymbol{\tau_{ini}}$, the USV will start to proceed towards the end point.
- While following the path, the USV will simultaneously monitor the positions and velocities of itself and other moving ships. The prediction algorithm will now be called to estimate the trajectory of the USV and other ships in next few time steps, to determine if there will be a collision risk.
- If the collision risk exits, a new path should be generated. The dynamic safety map $\boldsymbol{W_d}$ will be constructed around each moving obstacle.
- The $\boldsymbol{W_d}$ will then be merged with the safety map $\boldsymbol{W_s}$ as well as the original binary map $\boldsymbol{W_o}$ to generate a new synthetic map $\boldsymbol{W}$. Based on $\boldsymbol{W}$, a new path $\boldsymbol{\tau_{new}}$ will be sought by applying FMM again. $\boldsymbol{\tau_{new}}$ is the optimised trajectory without colliding with both static and dynamic obstacles in time step t, and the USV will follow it until the next waypoint has been reached.
- When the new waypoint is reached, the algorithm will determine if it is the final target point. If it is not, the algorithm will jump back to step 3 and move towards the next waypoint.

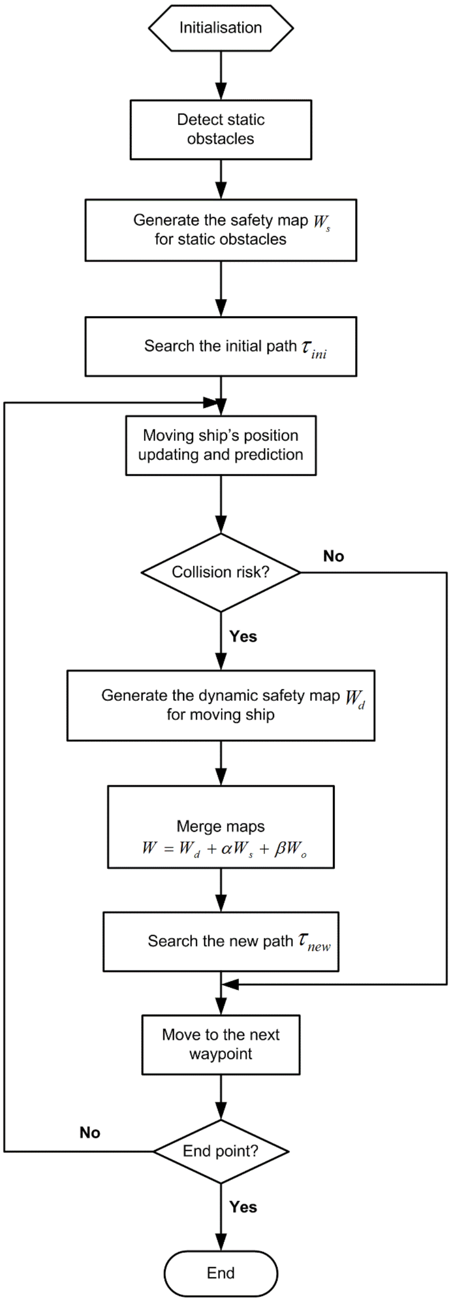

Fig.8 Flow chart of path planning algorithm for dynamic obstacle avoidance

5. Results

The section has been divided into three parts. Section 5.1 presents a practical trial on avoiding sensor failure; then the next section demonstrates a simulation result in AIS signal filtering and TS positions prediction; finally, the simulation results of the path planning algorithm for dynamic obstacle avoidance are illustrated and discussed.

5.1. Multi-sensor data fusion testing results

Practical trials were launched on Springer USV at Roadford Lake, Devon. Three different electronic compasses and a low-cost IMU were set up on the Springer USV and provided measurements as the inputs of the designed fuzzy MSDF system. The USV was operated in approximately 1.5 m/s. The sampling time for sensors to take measurements was 1 second. Three buoys were set up as waypoints, constituting a waypoint-tracking path for the USV as shown in Fig. 9(a).

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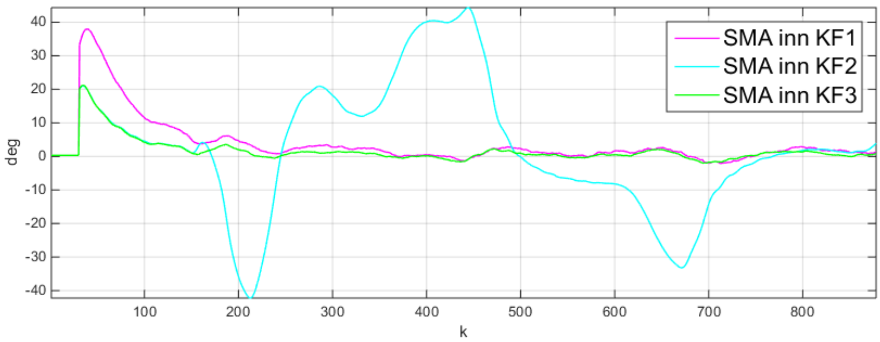

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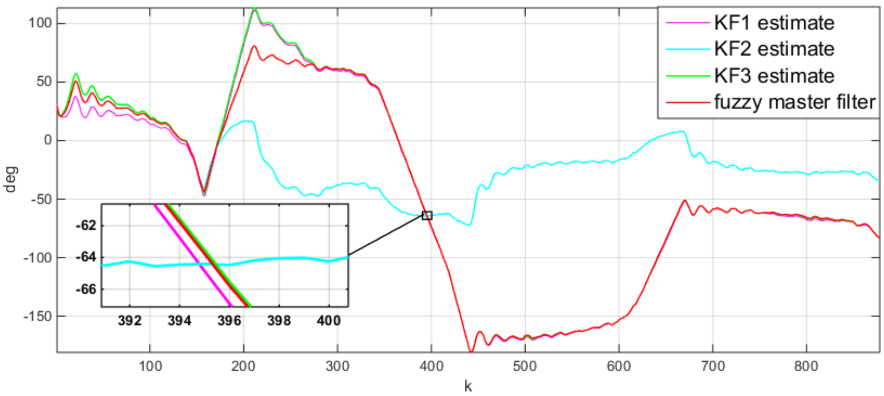


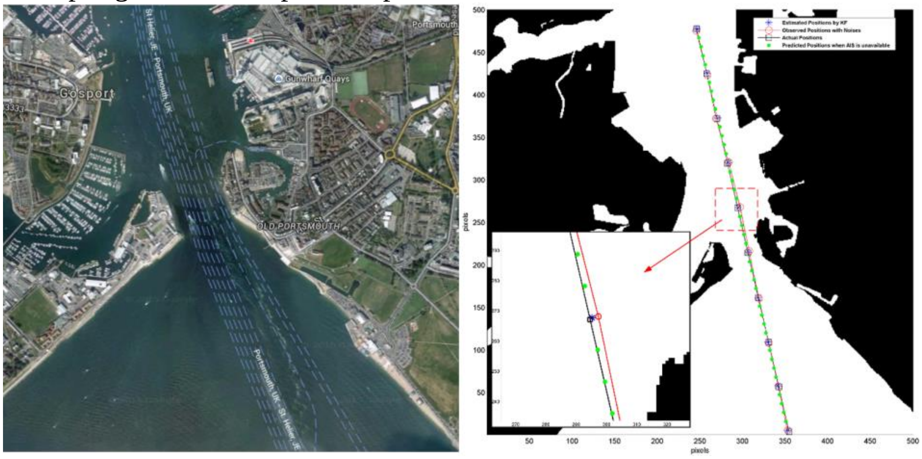
(c)

Fig. 9 Trial results for the fuzzy MSDF algorithm. (a) Testing area at the Roadford lake; (b) SMA of the innovations of each KF; (c) KF estimates of the headings and fuzzy data fusion estimates

To accomplish the set trajectory, the Springer USV made three turnings and steadily maintained four different headings as illustrated in Fig. 9(c). From Fig. 9(b), the SMA values of the innovations of the KF2 start to deviate largely from zero at time step k = 180, which indicates a malfunction of Compass 2. However, in Fig. 9(c), although the associated KF2 of Compass 2 gives incorrect estimations, the fuzzy master filter still gives a proper fused result in the presence of sensor failure. Due to the fact that in practical experiment, the actual headings of the USV are unpredictable, it is difficult to say whether the fuzzy master filter provides better results than the KFs. However, evidence does show that the fuzzy master filter can aggregate different fuzzy inputs and discard sensor malfunctions.

5.2. AIS detection & prediction

The simulation area is the Portsmouth Harbour. It has first been converted into a binary map, which has the dimension of 500 pixels * 500 pixels representing a 2.5 km * 2.5 km area (1 pixels = 5 m). The simulated TS is assumed to be operated in a constant speed and an invariable course via a straight line. AIS information update interval is simulated to be 1 minute and the total operational time is 10 minutes. The sampling time for the position prediction is assumed to be 12 seconds.



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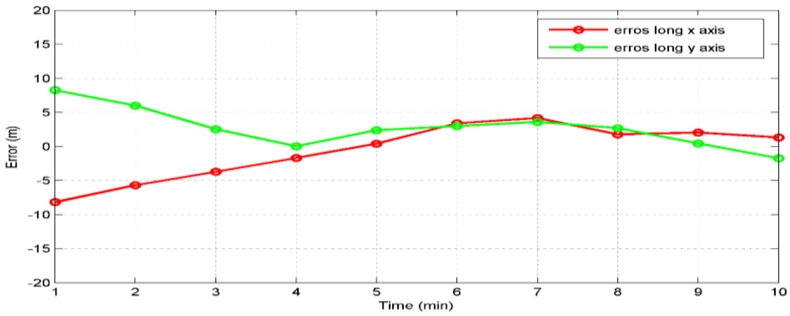

(b)

Fig. 10 Simulation results for target detection and predictions. (a) Simulation area around Portsmouth Harbour; (b) KF estimation errors in x and y axis

As demonstrated in Fig. 10(a), 5 possible positions (green dots) are predicted by the KF during each AIS data update interval and all the predictions are along the simulated trajectory, which proves that the algorithm is able to provide effective estimated positions without AIS measurement in the certain time period. In the meantime, 10 KF estimated positions are obtained after each AIS data update. From the enlarged figure, it is evidently that the KF offers a good performance for improving AIS data accuracy since the estimated positions (blue star) are closer to the actual positions (black line). It is further verified from Fig. 10(b), the position errors in x and y directions are reduced from almost 9m and start to fluctuate within a narrow range along the zero line. All the evidences indicates the KF algorithm for the AIS data is efficient for both detecting the TS and predicting its future positions.

5.3. Dynamic obstacle avoidance path planning

The area near Plymouth harbour shown in Fig. 11(a) is selected as the testing area, which has 2.5km*2.5km dimension. The selected area is first converted into a binary map as shown in Fig. 11(b) with 500*500 pixels dimension. To validate the capability of the algorithm dealing with complex traffic situations, three moving ships are added into the environment. The simulation configurations of the USV and the TSs are listed in Table 1. Algorithm’s prediction time period is set as 10, which means that the USV is able to estimate its own the movements as well as the TS for the next 10 time steps. Also, it is assumed the AIS’s transmission interval is every 5 time steps, which makes the USV unable to continuously perceive the TS’s position information thereby requiring position estimation.

Table 1 Simulation configurations for the USV and the moving TS

	USV	Target ship (TS)
Start point (m)	(26, 241)	(478,123)
End point (m)	(476,241)	(403,123)
Speed (knots)	10	9
Course	Depends on the path	180 degrees

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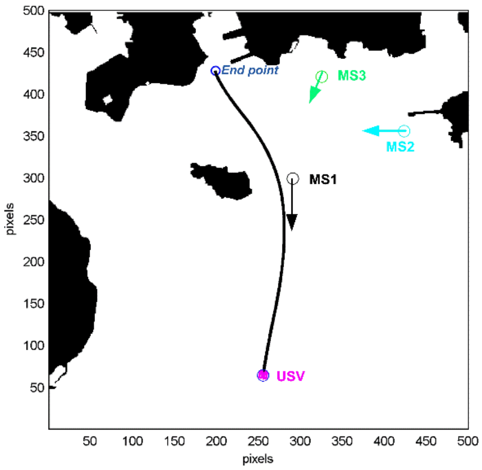

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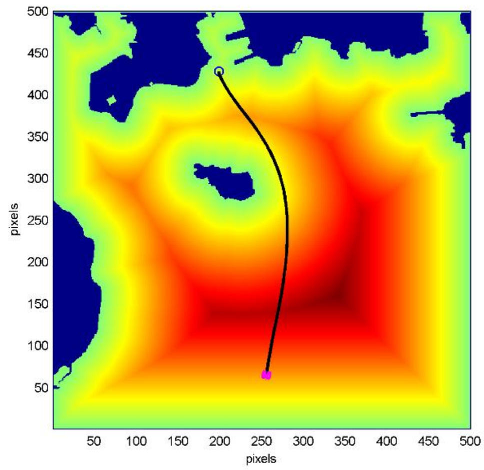

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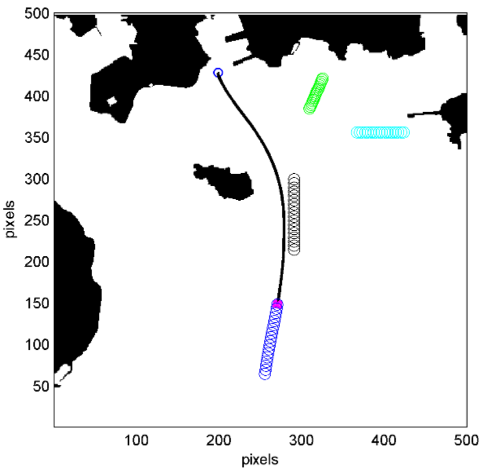

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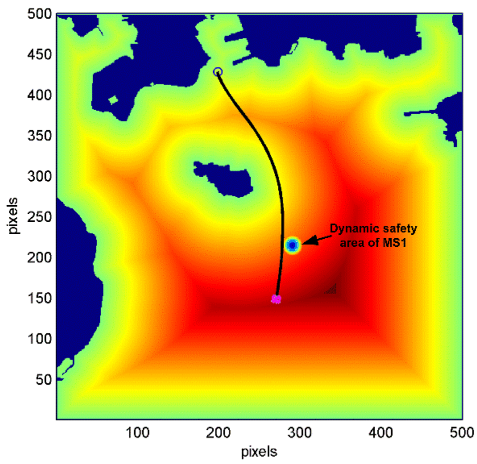

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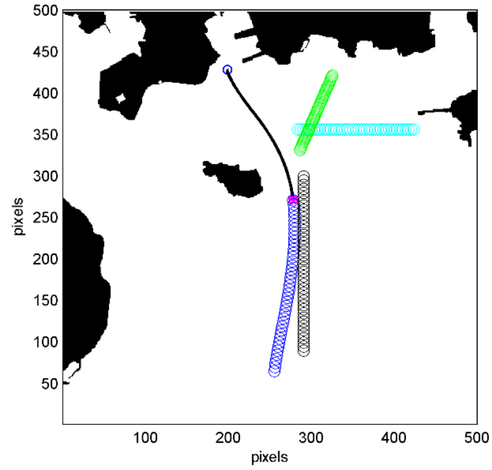
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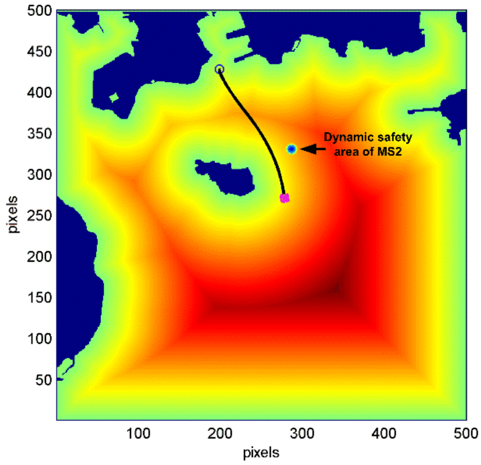
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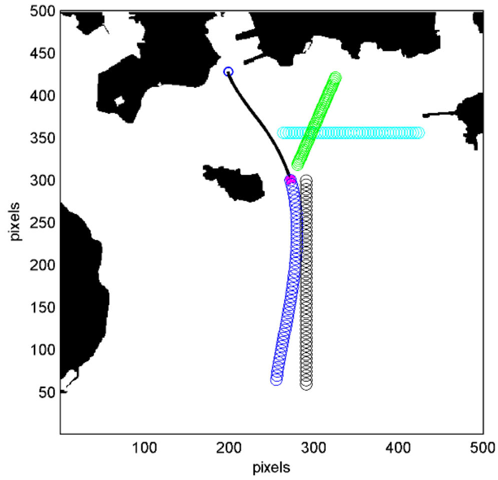
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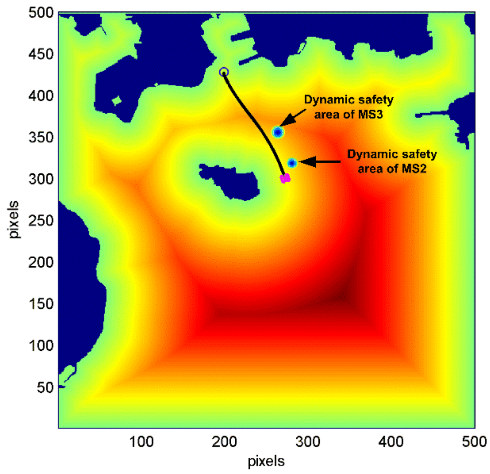
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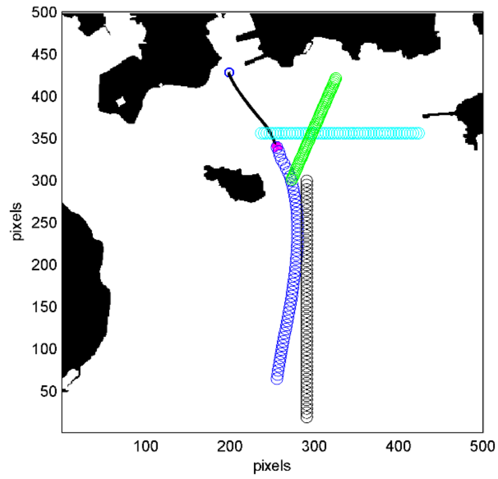
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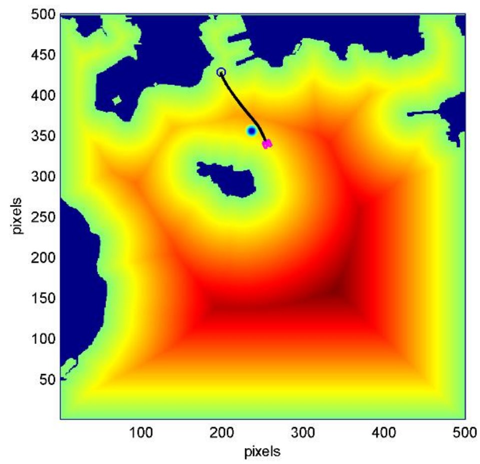
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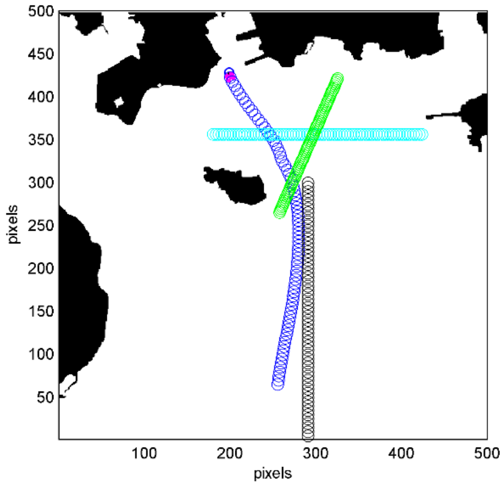
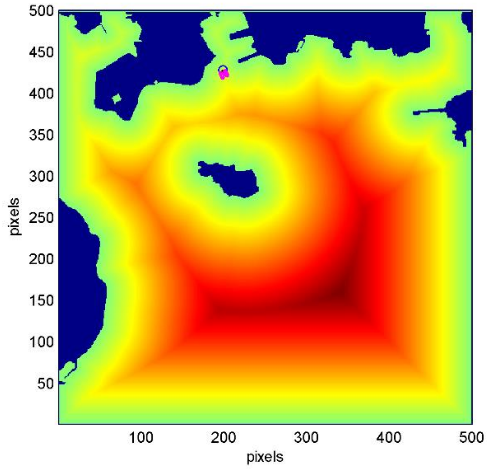
(k)



(l)



(m)

Fig. 11 Simulation results for path planning algorithm. (a) The simulation area near Plymouth harbor; (b) - (m) The sequence of movements of USV and its synthetic map at according time step

An initial guidance path is first generated by the algorithm and shown in Fig. 11(b) as the black line. At time step 18 (Fig. 11(d)), the collision risk with TS1 is identified by the USV; hence the dynamic safety area of TS1 is created and added into the synthetic map as $\boldsymbol{W}_{18}$ (Fig. 11(e)). The USV now re-plans its path to avoid the MS1. At time step 43, collision risk with MS1 no longer exists, but there is now a new possible collision risk with TS2. Therefore, only the dynamic safety area of TS2 emerges in the map as $\boldsymbol{W}_{43}$ (shown in Fig. 11(g)). As the USV proceeds, the traffic becomes more complicated, and at time step 52, TS3 starts to present a collision threat to the USV while TS2 is still collision risk, which makes the USV need to take actions to avoid both of these two ships. As shown in Fig. 11(i), dynamic safety areas for both TS2 and TS3 are integrated with $\boldsymbol{W}_{52}$. Based on $\boldsymbol{W}_{52}$, a collision free path avoiding both static and dynamic threats can be sought, which is shown as a black line in Fig. 11(i). Fig. 11(j) - Fig. 11(m) show how the USV avoids the TS3 and reaches the final target point.

6. Conclusions and future works

This paper improves the work of Liu et al. (2014) with a fuzzy multi-sensor data fusion algorithm and a predictive path planning algorithm. A practical application of the fuzzy MSDF algorithm is demonstrated and the results provide operational evidence of improving system robustness. Meanwhile, the simulation results show the newly designed path planning algorithm is capable of identifying collision risk and generating a new path in time to ensure obstacle avoidance. Future work to this research includes integrating a marine radar, generating an environmental map with both USV trajectory and dynamic TSs positions and considering environmental effects, e.g. current, wind in the path planning algorithm.

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