# Towards the Development of an Autonomous Navigation System for Unmanned Vessels

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This paper discusses the implementation of an intelligent navigation system for an autonomous unmanned surface vessel (USV). The focus is developing a multiple sensor data acquisition and fusion system to provide accurate and continuous information on positions, speeds and courses of the USV itself and also dynamic obstacles known as target ships (TSs). For USV's autonomous navigation, a Global Positioning System (GPS) receiver, low-cost sensors for dead reckoning (DR) and various types of electronic compasses are employed; For TS's localisation, the Automatic Identification System (AIS) information has been simulated to estimate and predict the positions of TSs over time. Simulations and practical trials are provided to demonstrate the effectiveness of the proposed system.

KEY WORDS
1. Multi-sensor data fusion  2. Kalman Filter  3. Fuzzy Logic

1. INTRODUCTION. Autonomous surface vehicles (ASVs) and unmanned vessels (UVs) are being developed by maritime industries to benefit military operations and to provide cheaper transport of cargos. Without deploying a human operator on-board, certain benefits are potentially achieved including low operating costs, reduced exposure of humans to risk and decreased energy consumption for most missions. Developing a robust autonomous navigation system provides a huge challenge for researchers and engineers that must overcome if ASVs or UVs are to become fully autonomous. A typical autonomous navigation system normally includes three different modules, i.e. data acquisition module (DAM), path planning module (PPM) and advanced control module (ACM). Figure 1 shows a typical structure of such system. The DAM acquires information about the own USV's position, speed, attitude etc. using various sensors such as Global Positioning System (GPS) receivers, sensors for dead reckoning (DR), electronic compasses and speed logs. The DAM also perceives the surrounding environment and obtains target ships (TSs) positions from the Automatic Identification System (AIS) and marine radar. A large amount of sensor data is obtained by the DAM 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 DAM, the PPM algorithm has the responsibility to generate a safe path (path planning) for the vessel. The generated safe path contains a set of waypoints, which are used by the ACM as reference points to guide the unmanned vessel with security. The purpose of the ACM is to ensure that the vessel adheres to the safe path by controlling rudder, propellers and thrusters.

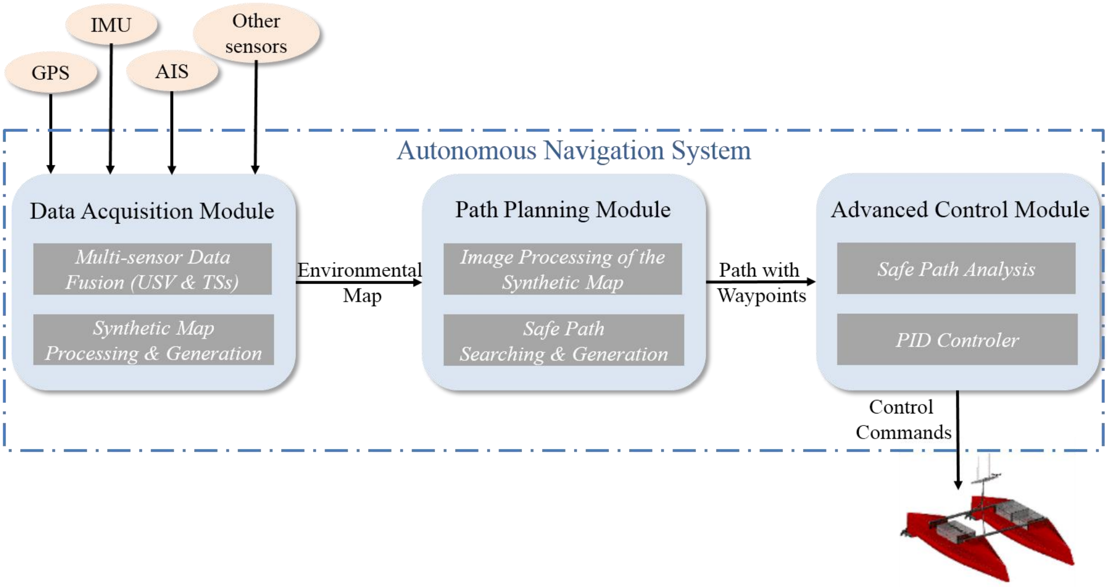


Figure 1 Navigation System Structure

In this paper, the DAM is detailed demonstrated. Inputs to this module are sensor data from GPS receiver, accelerometer, gyroscope, AIS receiver, radar and electronic compasses, and the output from this module is a navigation map of the dynamic environment. By using a number of marine sensors, the system will obtain large amount of navigational data with low accuracy and frequent disturbances. Therefore optimal estimation techniques are required to be applied as the core of the DAM to accomplish data fusion process. As shown in the schematic diagram (Figure 2), the DAM is built on an embedded hosting platform that incorporates the navigational data acquisition and fusion stages. Information accuracy from raw sensor measurements will at times be poor considering the sensor and equipment limitations and the environmental effects, so consistent and reliable data is likely to be compromised. An optimal estimation algorithm based on the Kalman filter (KF) techniques has therefore been developed and employed to improve signal accuracy. However, as its performance relies upon system reliability a fuzzy multi-sensor data fusion process is employed to enhance system robustness. Collision prevention sensors (e.g. AIS receiver, marine radar) are employed to detect dynamic obstacles around the USV, e.g. TSs. Before developing the data management process for AIS and radar information, the AIS data is first decoded and employed to make estimations and predictions of TSs' positions in this paper since it tends to give more reliable information as compared to the marine radar. The final stage will be to generate a synthetic map with all acquired data from previous processes.

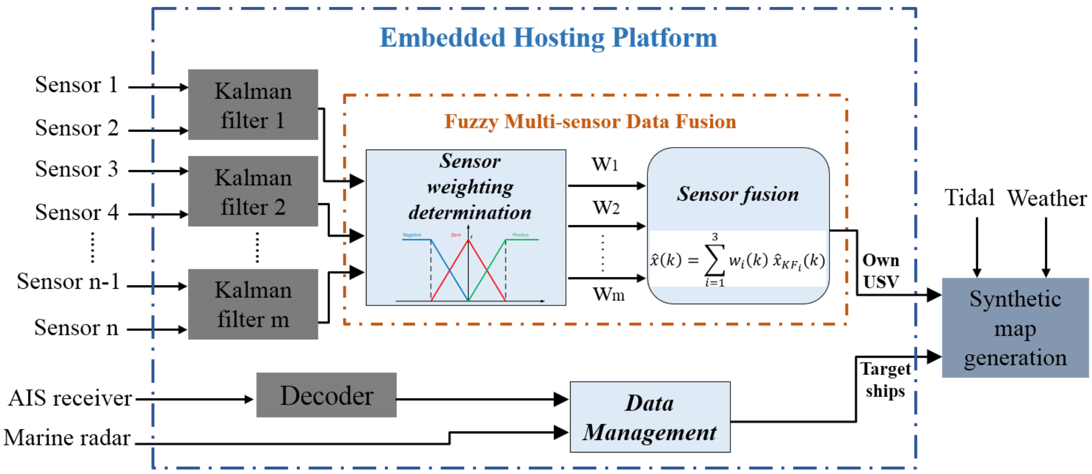


Figure 2 Data Acquisition Module Schematic Diagram

2 DAM: OWN USV DATA FUSION. Multi-sensor data fusion (MSDF) for OS's navigation is advancing in recent years; normally a multi-sensor navigation system is hybrid with both Global Navigation Satellite System (GNSS) and DR system. Most of these integrated systems employ a GPS receiver, several inertial sensors and maybe an electronic compass. Some advanced systems would also include sensors like an odometer or even a camera. Caron et al. (2007) proposed particle multi-data sensor fusion algorithms for land vehicle, and concentrated on observe 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 IMUs, which provide good performance on reducing GPS position error. Li et al (2014) also developed a GPS/INS/Odometer integrated system for a land vehicle, which can generate both accurate positions and speed information.

Compared to a land vehicle, ships at sea are normally operated at a constant speed and courses are almost the greatest cause of their positions change. Therefore, courses determination is particularly important in developing the navigation system of the USV. In this study, a GPS receiver, an inertial measurement unit (IMU) that composes DR sensors (accelerometer, gyroscope) and three different electronic compasses are employed to generate the own USV's navigational data, i.e. positions, speeds and courses. At the beginning of the system, all sensors are connected so the system reads data and applies appropriate conversions to establish a coordinate frame. The position measurements are provided by the GPS receiver, which measures the distance to the satellites by comparing the time difference of the signal transmitting to compute absolute positions; the course measurements are formed by electronic compasses, which measure the earth's magnetic filed to compute the USV's directions; the IMU provides acceleration and rotation rates of the USV to calculate its further positions and courses. Then proper optimal estimation techniques, e.g. the KF are applied to reduce sensors' errors and generate optimal estimated positions, speeds and courses of the own USV. Finally, a trajectory of the own USV will be produced based on those data.

2.1. *Kalman Filter Implementation*. The KF is a popular technique applied to navigation algorithms as an optimal estimator for linear stochastic system (Hu et al, 2003). In the Kalman filter, a standard stochastic-deterministic state-space set of equations is used to describe the predictive and measurement (observation) model pair as:

$$\begin{cases} \boldsymbol{x}(k) = \boldsymbol{A}\,\boldsymbol{x}(k-1) + \boldsymbol{B}\,\boldsymbol{u}(k-1) + \boldsymbol{w}(k-1) \\ \boldsymbol{z}(k) = \boldsymbol{H}\,\boldsymbol{x}(k) + \boldsymbol{v}(k) \end{cases} \tag{1}$$

where $x$ is the state vector; matrix $\boldsymbol{A}$ relates the previous state $\boldsymbol{x}(k-1)$ to the current state $\boldsymbol{x}(k)$; matrix $\boldsymbol{B}$ relates the optional control input $u$; matrix $\boldsymbol{H}$ relates state vector to the measurement $\boldsymbol{z}(k)$; $\boldsymbol{w}$ and $\boldsymbol{v}$ are assumed to be white noise sequences, normally distributed with zero mean and standard deviations, i.e. $p(w){\sim}N(0,Q), p(v){\sim}N(0,R)$. (Greg and Gary, 2011)

The recursive KF algorithm shown in Figure 3 involves an iterative process with two steps, prediction and estimation. With the initial estimate of the state vector $\hat{\boldsymbol{x}}(0)$ and its covariance $\boldsymbol{P}(0) = cov\{(\hat{\boldsymbol{x}}(0) - \boldsymbol{x}(0))(\hat{\boldsymbol{x}}(0) - \boldsymbol{x}(0))^T\}$, the predicted next state of system is calculated by the state equation, which is called Prediction or Time Update. Then the system introduces the measurement and estimates the optimal state by using the minimum mean square error (MMSE) method; this process is called Estimation or Measurement Update. After the optimal estimation, the system updates its covariance to reduce the error covariance, and loops back.

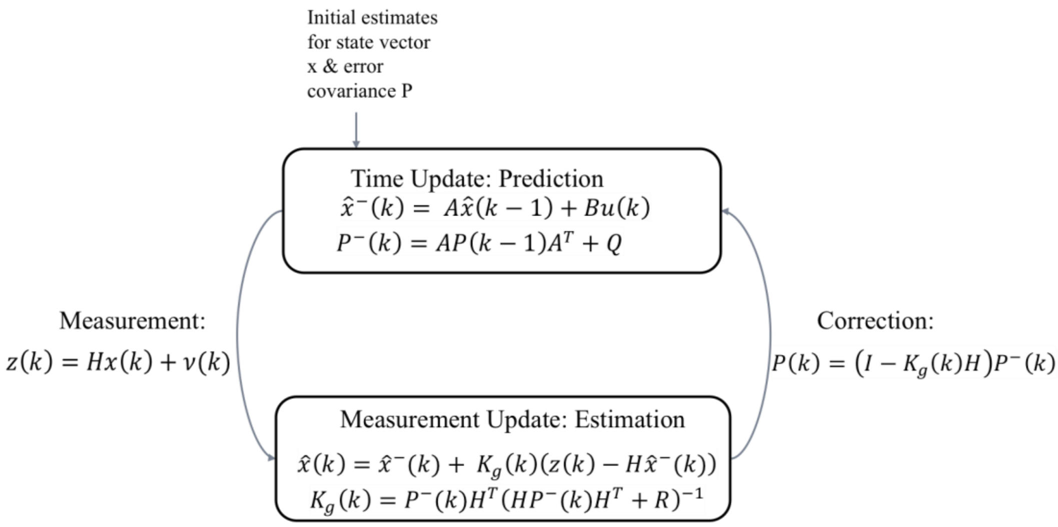


Figure 3 Kalman Filter Process

In this study, the KF is used to estimate the positions, velocities and courses of the own USV as well as the DR sensors' bias. Considering an USV navigating in a 2D configuration space, the GPS receiver and electronic compasses measure positions and courses information respectively, while DR sensors provide the acceleration and rotation rates. Let $A_i$ & $\omega_i$ represent the actual acceleration and rotation, the sensors' constant bias is $b$ and unpredictive processing errors are $w$; $A_o$ and $\omega_o$ denoting the accelerometer and gyroscope readings, can be given as:

$$\boldsymbol{A_o}(k) = \boldsymbol{A_i}(k) + \boldsymbol{b_a}(k) + \boldsymbol{w_a}(k) \tag{2}$$
$$\omega_o(k) = \omega_i(k) + b_g(k) + w_g(k) \tag{3}$$

The positions and courses of the vehicle can be obtained by discrete integration of the acceleration rate and rotation rate:

$$\boldsymbol{p}(k) = \boldsymbol{p}(k-1) + \frac{1}{2}{T_s}^2 \times \boldsymbol{A_i}(k) \tag{4}$$

$$\theta(k) = \theta(k-1) + T_s \times \omega_i(k) \tag{5}$$

where $T_s$ denotes the sampling time and $k$ is the number of time-steps. Substituting (2) and (3) into (4) and (5), Equation (4) & (5) can be rewritten as:

$$\boldsymbol{p}(k) = \boldsymbol{p}(k-1) + \frac{1}{2}{T_s}^2 \times [\boldsymbol{A_o}(k) - \boldsymbol{b_a}(k) - \boldsymbol{w_a}(k)] \tag{6}$$

$$\theta(k) = \theta(k-1) + T_s \times \left[\omega_o(k) - b_g(k) - w_g(k)\right] \tag{7}$$

The velocities of the USV can also be computed by the acceleration rate as:

$$\begin{aligned} \boldsymbol{v}(k) &= \boldsymbol{v}(k-1) + T_s \times \boldsymbol{A_i}(k) \\ &= \boldsymbol{v}(k-1) + T_s \times [\boldsymbol{A_o}(k) - \boldsymbol{b_a}(k) - \boldsymbol{w_a}(k)] \end{aligned} \tag{8}$$

For the positions determination, the state vector $x(k)$ is defined with the required information (positions and speeds) as

$$\boldsymbol{x} = \begin{bmatrix} p_x & p_y & v_x & v_y & b_x & b_y \end{bmatrix}^T \tag{9}$$

where $p_x$ and $p_y$ represent the position, $v_x$ and $v_y$ are velocities and $b_x$ and $b_y$ are the sensor bias in x and y direction respectively.

The known control input $\boldsymbol{u}(k)$ is the accelerometer readings at sampling time $k$ and $\boldsymbol{H}\,\boldsymbol{x}(k)$ represents the actual position of the vehicle at time $k$, $\boldsymbol{w}(k)$ and $\boldsymbol{v}(k)$ are random variables which represent the accelerometer and GPS measurement noise respectively. $\boldsymbol{z}(k)$ is the GPS reading with measurement error at time $k$:

$$\boldsymbol{z}(k) = \begin{bmatrix} p_x(k) \\ p_y(k) \end{bmatrix} + \boldsymbol{v}(k) \tag{10}$$

Therefore the state-space set of equations is determined by Equations (4), (6), (8), (9) and (10). It describes the propagation of positions, velocities, as well as the unchanging nature of bias as below:

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

For courses determination, the new state vector is defined as:

$$\boldsymbol{x} = [\theta \quad b]^T \tag{12}$$

where $\theta$ denotes the USV's course and b is the gyroscope bias.
The control input $u$ is represented by the gyroscope reading and the following state equation is determined by Equation (7) and (12).

$$\begin{bmatrix} \theta(k) \\ b(k) \end{bmatrix} = \begin{bmatrix} 1 & -T_s \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \theta(k-1) \\ b(k-1) \end{bmatrix} + \begin{bmatrix} Ts \\ 0 \end{bmatrix} \omega_o(k-1) + \boldsymbol{w}(k-1) \tag{13}$$

The compass reading, the new observation $z(k)$, on the other hand provides a direct measurement of the course angle of the vehicle, can be modelled as:

$$z(k) = \theta(k) + \nu(k) \tag{14}$$

2.2. *Fuzzy Multi-sensor Data Fusion (MSDF) System*. The DAM also includes a fuzzy multi-sensors data fusion algorithm 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 fusion filter or a sensor management process.

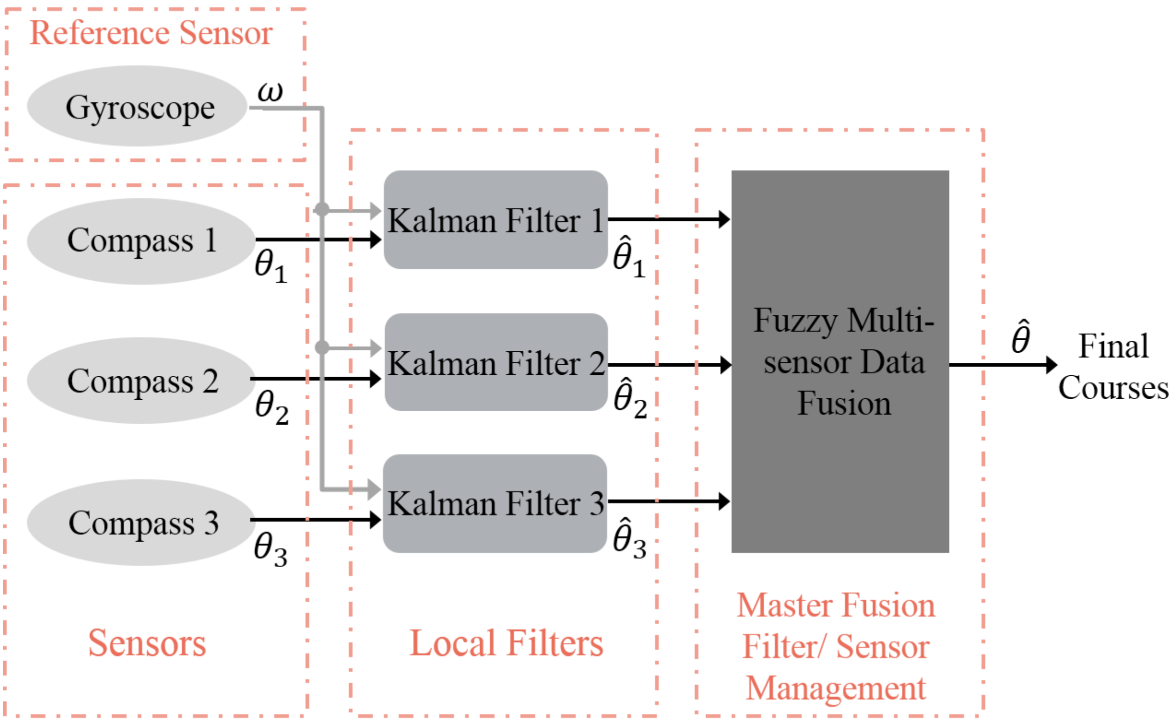


Figure 4 Federated Filter Architecture for the Fuzzy MSDF Algorithm

As Figure 4 demonstrates, three independent electronic compasses represent local sensors; and a gyroscope is used as the reference. Local filter employs the Kalman filter implemented in the previous section. The designed fuzzy MSDF algorithm acts as a master fusion process to cope with possible sensor failures, by assigning a weight to each of the local KF state estimates, as illustrated in Figure 5.

Figure 5 Fuzzy Multi-sensor Data Fusion Process

The fused state estimate is then computed as:

$$\hat{x}(k) = \sum_{i=1}^{3} w_i(k)\, \hat{x}_{KF_i}(k) \tag{15}$$

The decision making of the aforementioned weights is based on observation of the innovations sequence of each KF, where the innovations sequence of a KF is defined as:

$$\{inn(k)\} = \{z(k) - H\, \hat{x}(k)\} \tag{16}$$

that is the difference between the compass measurement and the predicted course 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). Therefore this sequence could be monitored to detect a failure in the correct estimation by one of the KFs. In order to monitor the innovations sequence, which in general is a random process and the individual value is meaningless, the simple moving average (SMA) of the innovations sequence of each KF is computed:

$$SMA(k) = \frac{inn(k) + inn(k-1) + \cdots + inn(k-K+1)}{K} \tag{17}$$

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

Negative function: $$\mu_N = \begin{cases} 1 & if\ SMA < SMAN \\ SMA/SMAN & if\ SMAN \le SMA < 0 \\ 0 & if\ SMA \ge 0 \end{cases} \tag{18}$$

Zero function: $$\mu_z = \begin{cases} 1 - SMA/SMAN & if\ SMAN \le SMA < 0 \\ 1 - SMA/SMAP & if\ 0 \le SMA \le SMAP \end{cases} \tag{19}$$

Positive function: $$\mu_P = \begin{cases} 0 & if\ SMA < 0 \\ SMA/SMAP & if\ 0 \le SMA < SMAP \\ 1 & if\ SMA \ge SMAP \end{cases} \tag{20}$$

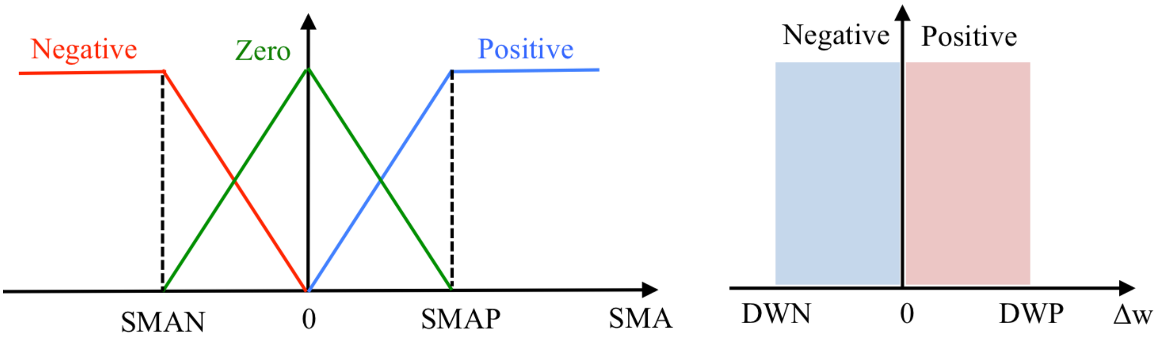

Figure 6 Input & Output Membership Functions

As indicated by the output fuzzy membership functions (Figure 6), the output to the fuzzy logic inference system is chosen to be a change in the weight of the filter, $\Delta w$, rather than the weight itself. This is to avoid brusque transitions in the overall estimate.

Based on the afore described membership functions, the following fuzzy rules are established:

*Rule 1*: If SMA negative then $\Delta w$ is negative
*Rule 2*: If SMA is zero then $\Delta w$ is positive
*Rule 3*: If SMA is positive then $\Delta w$ is negative

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

$$\Delta w^* = \frac{\int \mu_i \, \Delta w \, d\Delta w}{\int \mu_i \, d\Delta w} \tag{21}$$

where $\mu_i$ represents the membership function ($\mu_N$, $\mu_Z$, or $\mu_P$), $\Delta w^*$ is the defuzzified output and $\Delta w$ is the output variable.
Once the $\Delta w$ 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 the weights themselves remains one,

$$\Delta w_{i,n}(k) = \Delta w_i(k) - \frac{1}{3}\sum_{j=1}^{3} \Delta w_j(k), \qquad i = 1,2,3 \tag{22}$$

The resultant updated weights of each filter is given by:

$$w_i(k) = w_i(k-1) + \Delta w_{i,n}(k), \qquad i = 1,2,3 \tag{23}$$

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. DAM: TARGET SHIPS DETECTIONS. TSs navigational data fusion has analogous process as the own USV. But the data are obtained from different sensors; and require different data conversion and decoding process. In this paper, an AIS receiver, a collision avoidance sensor, is simulated to determine surrounding dynamic obstacles' positions as well as to predict their positions during the AIS data-transmitting intervals.

3.1 *AIS Data Decoding*. 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 provide 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, odometer and electronic compasses, etc. Voyage related information that includes ship's destination, Harzardous 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. Figure 7 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 need to be converted from the decimal values to corresponding ASCII characters.

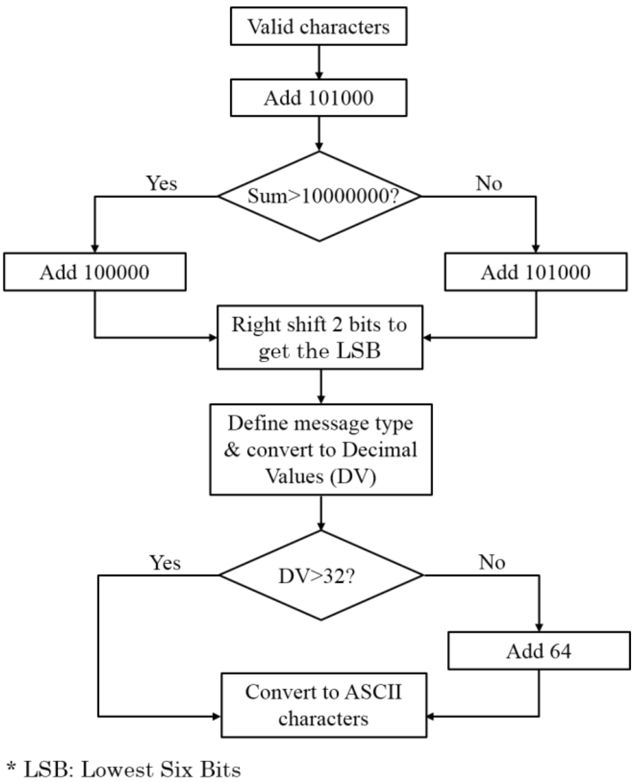


Figure 7 Flow chart of AIS Data Decoding

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 TSs' 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. The real time positions of this TS is required for the PPM to generate a safe path to avoid the collision. Hence, the system state vector can be defined as following:

$$x = [p_x \ \ p_y \ \ v_x \ \ v_y]^T \tag{24}$$

where $p_x$ and $p_y$ represent the positions, $v_x$ and $v_y$ are velocities in x and y direction. As mentioned in section 2.1, the KF employs a prediction model and measurement model pair (Equation (1)). Then the state equation of the TS positions determination can be determined with the matrixes below:

$$A = \begin{bmatrix} 1 & 0 & T_s & 0 \\ 0 & 1 & T_s & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, B = \begin{bmatrix} \frac{T_s{}^2}{2} & 0 \\ 0 & \frac{T_s{}^2}{2} \\ T_s & 0 \\ 0 & T_s \end{bmatrix} \tag{25}$$

where $T_s$ is the sampling period and the control input $u(k)$ is defined as:

$$u(k) = [\alpha_x(k), \alpha_y(k)]^T \tag{26}$$

where $\alpha_x$ and $\alpha_y$ 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:

$$z(k) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} x(k) + v(k) \tag{27}$$

During each AIS information update interval, the KF algorithm only executes the Prediction process shown in Figure 3 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.

4. RESULTS & DISCUSSIONS. This section is divided into two parts. The developed multi-sensor data fusion algorithm, was tested in practical trials; and the designed TS detecting and its positions predicting algorithm was simulated.

4.1. *Practical Trial Results*. Practical trials were launched on Springer USV at Roadford lake, Devon in April, 2014. It was a cloudy day with drizzles and the wind speed was 1-3.2m/s west. Three different electronic compasses, a GPS receiver, a low-cost IMU that consists of DR sensors were set up on the Springer via serial connections, as the input of the designed fuzzy MSDF system. The USV was operated in approximately 1.5 m/s and the duration for one trial was around 20 minutes. 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.

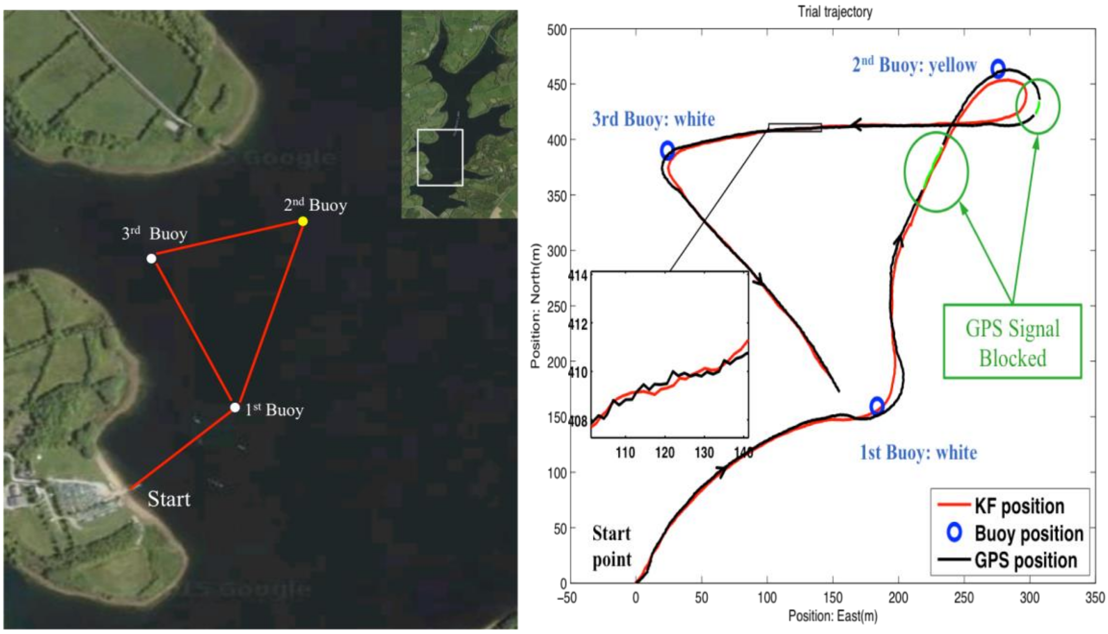


Figure 8 Trial results for USV trajectory with three buoys and signal blockage

As indicated in the trajectory in Figure 8, the USV came across sequentially three waypoints and returned back to the first one. GPS raw measurements were manually blocked for the two short time periods (as highlighted by the green circles in Figure 8). In actuality, the USV hit the 1$^{st}$ white buoy while bypassed the other two; whereas the raw GPS positions (black line) indicate differently. As opposite to the raw GPS positions, the KF estimated positions match the practical situation. Note also from the enlarged figure, the raw GPS measurements fluctuate all the time while the KF estimation can provide much smoother results. In addition, the KF estimations are able to recover the trajectory while the GPS signal had been blocked (indicated by the reproduction of trajectory when GPS signal is unavailable).

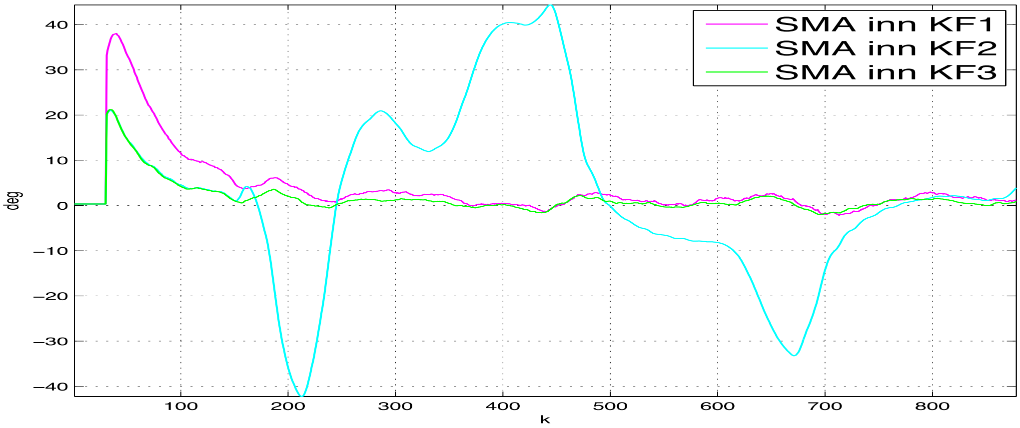


Figure 9 Trial results: SMA of the innovations sequence of each KF

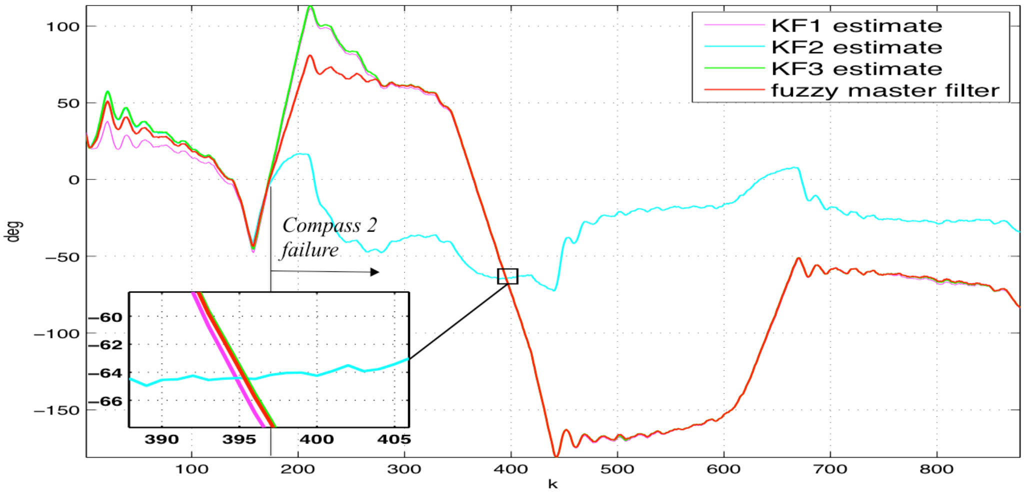


Figure 10 Trial Results: KF estimates of the course and fuzzy data fusion estimates

At time step k = 180, the SMA values of the innovations of the KF2 start to deviate largely from zero (Figure 9), which indicates malfunctions of Compass 2 since then. As shown in Figure 10, 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 courses of the USV are unpredictable, it is ambiguous to tell whether the fuzzy master filter provides better results than any KFs. However, evidence does show that the fuzzy master filter can aggregate different fuzzy inputs and discard sensor malfunctions.

4.2. *Simulation Results*. 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.

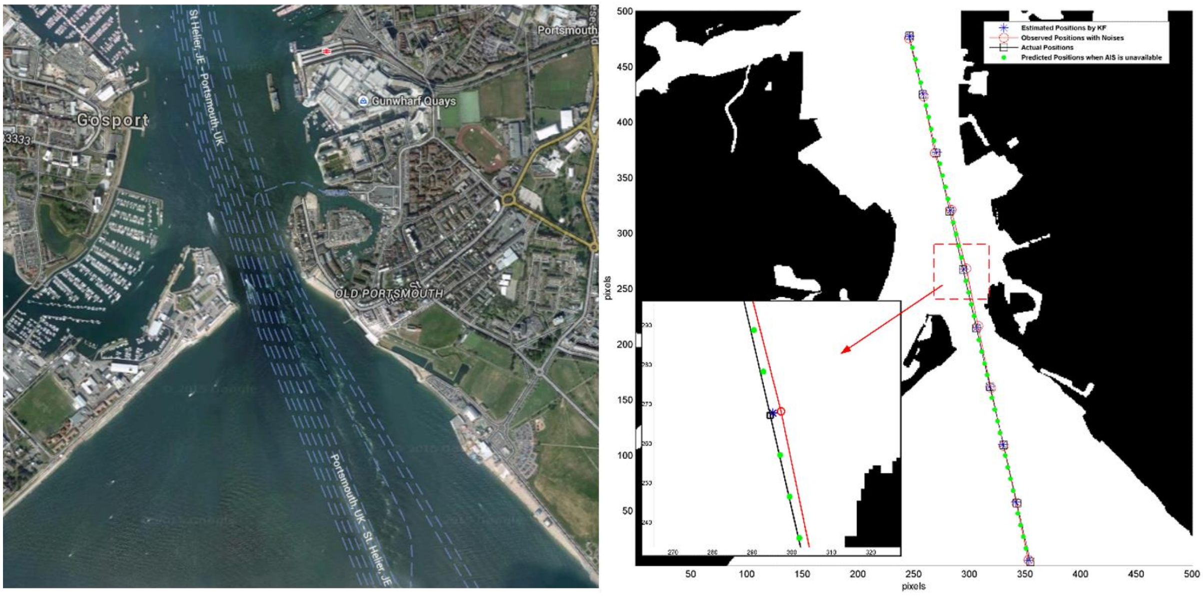


Figure 11 Simulation Results: KF estimates and predictions for a moving TS

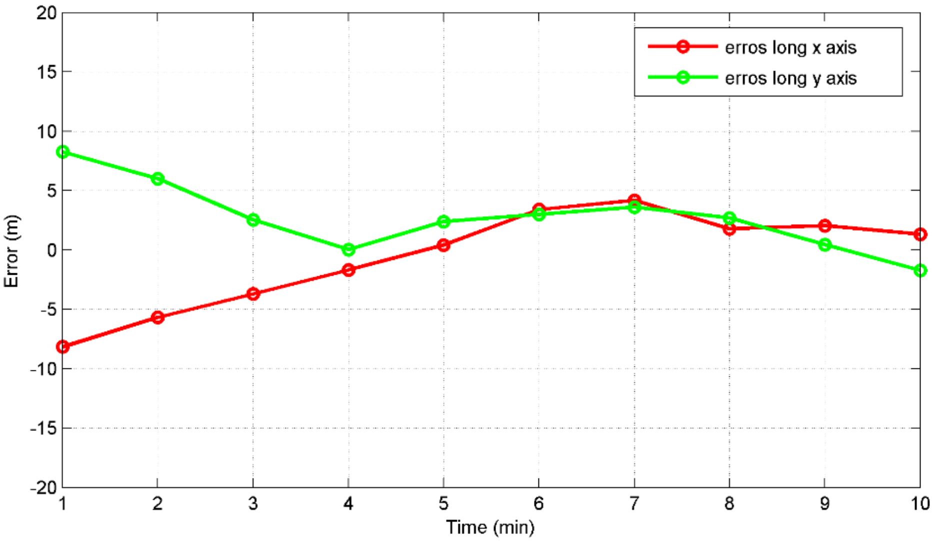


Figure 12 Simulation Results: KF estimation errors in x and y axis

As demonstrated in Figure 11, 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 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 enlarge figure, it is evidently that the KF has a good performance on improving AIS data accuracy since the estimated positions (blue star) are closer to the actual positions (black line). It is further verified from Figure 12, the position errors in x and y directions are reduced from almost 9 meters and start to fluctuate within a narrow range along the zero line. All the evidences indicate the KF algorithm for the AIS data is efficient for both detecting the TS and predicting its positions.

5. CONCLUSIONS & FUTURE WORK. In this paper, the sensor data managements for identifying own USV's navigational information as well as detecting the moving TS are demonstrated. The developed data acquisition and fusion system can recover the trajectory of the USV when GPS signal is unavailable in a short time interval; improve GPS data accuracy by analysing error covariance of the raw data to reduce unpredicted sensors error; distribute the weights of the estimations from each KF automatically by analysing the innovation sequences and produce continuous final optimal estimation for the USV course; reduce AIS measurement error and make predictions for TSs positions in the AIS data updating intervals to assist the PPM. Future work upon this study should include the data merging and fusion process for the AIS and the marine radar as well as the synthetic map generation.

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