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Design of an EKF-CI based Sensor Fusion for Robust Heading Estimation of Marine Vehicle

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An efficient approach for deriving accurate pose and heading values through multi-sensor fusion of data from several inexpensive sensors (such as multiple GPS (Global Positioning Systems), EC (electronic compass), rate gyro) is presented. The proposed multi-sensor fusion approach is composed of several sub-methods namely initial heading calculation, classification and weighing (CnW), extended Kalman filter (EKF) and then covariance intersection (CI) algorithms. The consecutive implementation of the sub-methods gives an accurate heading value with lesser RMSE (root mean square error) compared to the original GPS COG (course over ground) and EC. Several experimental tests were done to confirm the good performance of the proposed process.

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1. Introduction

The derivation of accurate data reading from multiple sensors is a very interesting topic not just for academic researchers but also for the people in the industry. Global Positioning Systems (GPS), electronic compass (EC), inertial measurement unit (IMU), decoders, cameras, radar, sonar and laser are some of the more common devices used. Several methods of sensor fusion are in use such as dead-reckoning,[1] weighing,[2] numerical integration,[3,4] fuzzy logic,[5] Kalman Filter (KF) or its variations,[6,7] Timing Synchronization,[8] Neural Network.[9] Combining several methods for better performance were also worked on such as Fuzzy and Kalman Filter,[10] Particle and Extended Kalman Filtering (EKF),[11] Weighing and Kalman.[12] Usually, the Kalman filter based fusion filters require to calculate the cross-covariance of local state estimation errors. In many theoretical and application problems, however, the computation of cross-covariance matrices is not trivial, but the computation is very complicated. The above drawback can be mitigated by applying the covariance intersection (CI)[13] fusion filtering, which allows to avoid the computation of the local cross-covariance and lead to solving the multi-sensor fusion problems with unknown cross-covariance. The CI algorithm gives an estimate of the mean and the covariance from the convex combination of the means and covariances.

This paper delves into the utilization of weighing, EKF and CI in the derivation of accurate heading data from multiple inexpensive GPS devices, EC and IMU. The proposed process initially calculates the heading data from the GPS position values using Forward Azimuth (FAz). It is then followed by a Classification and Weighing (CnW) method inspired by Ercan's[2] work. The result of this classification is used in the weighing step that merges the three GPS heading values with the EC reading. The computed GPS position, heading and covariance error matrix serves as the input to an EKF process whose result is then passed to the CI process to derive the final heading value.

A theoretical background on the different utilized as well as the proposed process is presented in Section 2. Section 3 details the experimental test setup and the corresponding step-by-step results for each of the sub-methods as well as the overall process. The concluding remarks are given in Section 4.

2. Theoretical Backgrounds

2.1 Heading derivation

Three methods (Direct arc tangent, FAz and centroid) were initially selected to check which one gave the best result with FAz emerging at the best choice. Azimuth is defined by the US Army as the angle between the line formed by two points and the North direction as reference that is measured in a clockwise direction. The formula for

FAz method is given in Eq. (1) noting that the initial position value set as (lat_2, $long_2$) and next position value as (lat_1, $long_1$) so that the initial heading angle (ψ) will be derived.

$$\begin{aligned}&\arg_i = \sin\Delta long \times \cos lat_2\\&\arg_2 = \cos lat_1 \times \sin lat_2 - \sin lat_1 \cos lat_2 \Delta long\\&\psi = \tan^{-1}(\arg_1, \arg_2) + 180\end{aligned} \tag{1}$$

2.2 Classification and weighing (CnW)

A classifying method to check the quality of the data from the GPS is developed based on the HDOP (horizontal dilution of precision) and Fix (fix quality of GPS data) values. The classification described in www.gpsinformation.org/dale/nmea.htm is utilized as follows: "0" is Invalid, "1" is for GPS Mode/ Standard Positioning Service, "2" is Differential GPS Mode, "3" signifies Precise Positioning System, "4" is Real Time Kinematic, "5" is for Float Real Time Kinematic, "6" is Estimated Fix/ dead reckoning, "7" is Manual input mode, while "8" signifies Simulation mode. The HDOP value is classified as: "0 < HDOP ≤ 1" gives an "Ideal" heading value, "1 < HDOP ≤ 2" is "Excellent", "2 < HDOP ≤ 5" is "Good", "5 < HDOP ≤ 10" is "Moderate", "10 < HDOP ≤ 20" is "Fair", and "20 < HDOP" is "Poor". The combination of HDOP and FIX values are then organized into the following classification:

If (HDOP is 1 to 2) and (FIX is 2 to 5) then IDEAL;
If (HDOP is 1 to 2) and (FIX is 1) then EXCELLENT;
If (HDOP is 3 to 5) and (FIX is 2 to 5) then EXCELLENT;
If (HDOP is 3 to 5) and (FIX is 1) then GOOD;
If (HDOP is 6 to 10) and (FIX is 2 to 5) then GOOD;
Else BAD;

The resulting classification from the HDOP and FIX combination are then assigned the following values as weights: "3" – Ideal,"2" – Excellent, "1" – Good, and "0" – Bad. These values are then utilized in Eq. (2) for the calculation of the heading values from the GPS and EC.

$$\begin{aligned}&h_{fused} = (h_{allGPS})(w_{allGPS}) + (h_{EC})(w_{EC})\\&h_{allGPS} = \frac{\Sigma_1^n (w_i h_i)}{\Sigma_1^n w_i},\ \ w_{allGPS} = \frac{\Sigma_1^n w_i}{n \times idealValue},\ \ w_{EC} = (1 - w_{allGPS})\end{aligned} \tag{2}$$

where:

n - total number of GPS
$idealValue$ - weight assigned for IDEAL status
h_{fused} - fused GPS and EC heading
h_{EC} – heading value of the EC
w_{allGPS} - overall weight of combined calculated GPS heading value
w_{EC} - weight of EC
h_{allGPS} - overall heading for "n" number of GPS
w_i - weight assigned for "i^{th}" GPS
h_i - calculated heading value for "i^{th}" GPS

The resulting value h_{fused} will be labeled as the "*GPSEC_yaw*" for future reference in the succeeding sections.

2.3 Extended kalman filter

The extended Kalman filter is used to obtain the state estimate with four general steps: (i) prediction of the state and the error covariance, (ii) computation of the Kalman gain, (iii) time update of the estimate, and (iv) time update of the error covariance. The controllability and observability of the KF or EKF have been proved and well known, the readers are requested to check on papers that dealt with this study such as that of Southall,[14] Kamrani[15] and Elizabeth.[16]

The nonlinear dynamic and measurement models are given as

$$x_{k+1} = f(x_k) + w_k \tag{3}$$

$$z_k = h(x_k) + v_k \tag{4}$$

where x_k is the state estimate and z_{kk} is the measurement. Q_k and R_k are the process noise and the measurement noise covariance matrix, respectively, and assumed to be positive definite. In this work, EKF is utilized due to the non-linearity of the system. The predicted state $\hat{x}_{k+1}^-$ and the predicted state error covariance P_{k+1}^- of the dynamic model are computed by

$$\hat{x}_{k+1}^- = f(\hat{x}_k^+) \tag{5}$$

$$P_{k+1}^- = F_k P_k F_k^T + Q_k \tag{6}$$

where F_k is the Jacobian matrix of the nonlinear dynamic model, P_k is the updated state covariance matrix in the previous time step, k, and the predicted measurement $\hat{z}_{k+1}^-$ is obtained by $\hat{z}_{k+1}^- = h(\hat{x}_{k+1}^-)$. The innovation covariance P_{k+1}^W of the residual error vector between the observed and predicted measurements is obtained by

$$P_{k+1}^W = P_{k+1}^{yy} + R_{k+1} = H_{k+1} P_{k+1}^- H_{k+1}^T + R_{k+1} \tag{7}$$

where $P_{k+1}^{yy} = H_{k+1} P_{k+1}^- H_{k+1}^T$ is the output covariance matrix, and H_{k+1} is the Jacobian matrix of the nonlinear measurement function $h(\hat{x}_{k+1}^-)$ evaluated about the predicted state $\hat{x}_{k+1}^-$, and R_{k+1} is the sensor measurement noise covariance matrix at the time, k+1.

Now the Kalman gain is computed by

$$K_{k+1} = P_{k+1}^{xy} (P_{k+1}^{vv})^{-1} = P_{k+1}^- H_{k+1}^T (P_{k+1}^{vv})^{-1} \tag{8}$$

The Kalman gain is calculated by multiplying the predicted cross-correlation matrix and the inverse of the innovation covariance matrix. Note that in the EKF algorithm the state distribution is approximated by a Gaussian random variable, which is then propagated through the first-order linearization of the nonlinear functions.

The state vector x_k of the dynamic model consists of the latitude, longitude, and heading elements, $x_k = [x_N, y_E, \psi]^T$, described by

$$\begin{aligned}\dot{x} = \begin{Bmatrix}\dot{x}_N\\ \dot{y}_E\\ \dot{\psi}\end{Bmatrix} &= \begin{bmatrix}cos\psi & -sin\psi & 0\\ sin\psi & cos\psi & 0\\ 0 & 0 & 1\end{bmatrix}\begin{Bmatrix}u\\ v\\ r\end{Bmatrix} + w\\ &= \begin{bmatrix}u\cos\psi + v\sin\psi\\ u\sin\psi + v\cos\psi\\ r\end{bmatrix} + w = f(x) + w\end{aligned} \tag{9}$$

The measurement model $h(x_k) = H_k$ is given by

$$y_k = \begin{Bmatrix} x_{N,k} \\ y_{E,k} \\ \psi_k \end{Bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{pmatrix} x_{N,k} \\ y_{E,k} \\ \psi_k \end{pmatrix} = H_k x_k + v_k \quad (10)$$

Note that the measurement values are measured from three different GPS sensors and one digital compass to estimate the state which consists of the latitude, longitude as well as the heading angle. The process noise covariance matrix Q and measurement noise covariance matrix R are set based on tests done on the measured values as

$$Q = \begin{bmatrix} 0.01 & 0 & 0 \\ 0 & 0.01 & 0 \\ 0 & 0 & 10 \end{bmatrix}, \; R_k = \begin{bmatrix} 0.3 & 0 & 0 \\ 0 & 0.07 & 0 \\ 0 & 0 & 0.03 \end{bmatrix} \quad (11)$$

2.4 Sensor fusion with covariance intersection algorithm

Multiple GPS, EC and IMU sensor data are collected and fused to extract precise pose and heading information. Multisensor information fusion filtering has been widely applied to various applications, including integrated navigation, robot motion planning and so on. Common methods used for multi-sensor information fusion is either centralized or distributed Kalman filtering approaches.[17] The Kalman filter based fusion filters require the calculation of the cross-covariance of local state estimation errors. In many theoretical and application problems, however, the computation of cross-covariance matrices is not trivial, but the computation is very complicated. The above drawback can be mitigated by applying the CI[13] fusion filtering, which avoids the computation of the local cross-covariance and lead to solving the multi-sensor fusion problems with unknown cross-covariance. The CI algorithm gives an estimate of the mean and the covariance from the convex combination of the means and covariances. The general form of the CI algorithm is given as

$$\begin{aligned} P_{cc}^{-1} &= \omega P_{aa}^{-1} + (1-\omega) P_{bb}^{-1} \\ P_{cc}^{-1} c &= \omega P_{aa}^{-1} a + (1-\omega) P_{bb}^{-1} b \end{aligned} \quad (12)$$

where a and b are the input estimates of the mean values, P_{aa} and P_{bb} are the input estimates of the covariances, c and P_{cc} are the fused state estimate of the means and covariances, and ω is the weight utilized to optimize the update ($0 \le \omega \le 1$). For the case of multiple observations, the covariance intersection filter can be further extended by using the concept of the convex combination given by

$$P_0^{-1} = \sum_{n=1}^{n} \omega_n P_n^{-1} \quad (13)$$

$$P_0^{-1} \hat{x}_0 = \sum_{n=1}^{n} \omega_n P_n^{-1} \hat{x}_n \quad (14)$$

where ($0 \le \omega_n \le 1$) and $\omega_1 + \omega_2 + \ldots + \omega_n = 1$.

In this work, the covariance intersection filter is applied in order to fuse the three different GPS observations for robust estimates of the heading and pose of a marine vehicle. The state consists of

$$c = \begin{Bmatrix} lat' \\ long' \\ yaw' \end{Bmatrix} = \begin{Bmatrix} N' \\ E' \\ \psi' \end{Bmatrix} \quad (15)$$

The system state covariance (uncertainty) P is a matrix of size 3x3 with the description for each element described as follows

$$P_i = \begin{pmatrix} P_{11,i} \, P_{12,i} \, P_{13,i} \\ P_{21,i} \, P_{22,i} \, P_{23,i} \\ P_{31,i} \, P_{32,i} \, P_{33,i} \end{pmatrix}, \; i = 1, 2, 3 \quad (16)$$

where

P_{11} = uncertainty (variance) in latitudinal velocity
P_{22} = uncertainty in longitudinal velocity
P_{33} = uncertainty in yaw angular velocity
P_{12} = covariance in latitudinal/ longitudinal velocities
P_{13} = covariance in latitudinal/ yaw angular velocities
P_{21} = covariance in longitudinal/ latitudinal velocities
P_{23} = covariance in longitudinal/ yaw angular velocities
P_{31} = covariance in yaw angular/ latitudinal velocities
P_{32} = covariance in yaw angular/ longitudinal velocities

2.5 Proposed multi-sensor fusion algorithms

The GPS and EC utilized had a sampling frequency of 10Hz while the IMU was at 100Hz. Data were read from each individual sensor in their own specific rate which were then utilized for the heading derivation via FAz (GPS data), classification and weighing (GPS and EC data), extended kalman filtering (CnW result, GPS and IMU data) and covariance intersection (EKF result). The prediction and update process of the EKF is performed by using one data set each for GPS (FAz and *GPSEC_yaw* heading data) and EC with one hundred data samples from the IMU. This was designed to continuously incorporate the changes as detected by the IMU with the current data reading of the GPS and EC.

In this algorithm, after the proposed method processes FAz, CnW steps, then, CI filtering algorithm fuses multiple GPS data, EC and IMU values to obtain a sub-optimal or near optimal estimates as following the step-by-step process below:

(1) Calculate GPS heading values, *GPSi_yaw*, using FAz if valid GPS value available.

(2) Evaluate the individual GPS values (if any) using CnW.

(3) Combine the multiple calculated GPS and EC heading values using second part of CnW stage to derive *GPSEC_yaw*.

(4) Any GPS with invalid heading value will be assigned the *GPSEC_yaw* as its value (*GPSi_yaw* = *GPSEC_yaw*)

(5) Perform EKF for each of the GPS fused with the IMU values. The accelerometer value will be interepreted as local measurements of the local gravity vector.[18] The inputs are lat_i, $long_i$, *GPSi_yaw* and covariance matrix *PCI*. The output values are lat_i_EKF, $long_i\_EKF$, psi_i_EKF and covariance matrix *P_EKF*.

(6) Perform CI with EKF output as the input. The output values are *lat_CI*, *long_CI*, *psi_CI* and covariance matrix *PCI*. The final fused heading value would be *lat_C*I while *PCI* is passed as an input to the next iteration of the method.

(7) Go back to step (1) for next set of GPS, EC and IMU values.

3. Experimental Tests

Two runs were conducted on different days with different weather conditions on the same location to incorporate the environmental

Table 1 RMSE with no missing data for all the GPS

	Run I	Run II
GPS#1/ #2/ #3 (COG)	0.5483, 0.5037, 0.4966	0.8183, 0.5616, 0.5997
Average of GPS COG	0.5052	0.6211
GPS only CnW	0.4260	0.4960
Electronic Compass	1.6551	10.5466
GPSEC_yaw CnW	0.4260	1.2855
EKF-CI	0.4330	0.5122

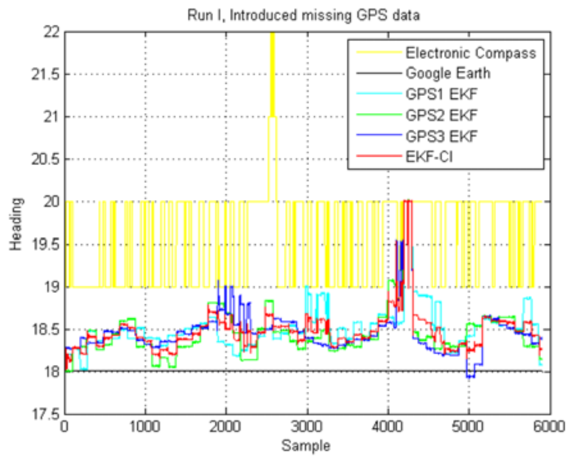

Fig. 1 Heading RMSEs with GPS data outage introduced (Run I)

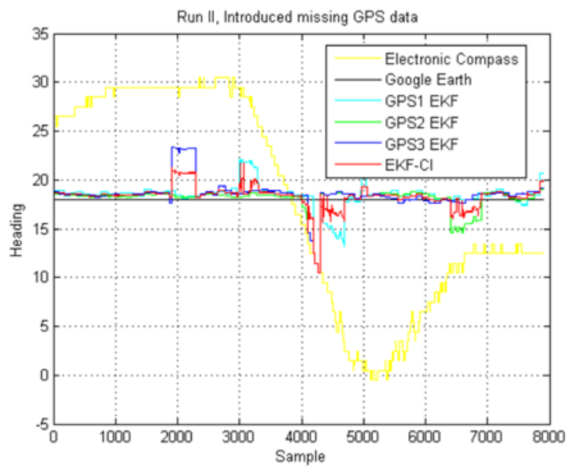

Fig. 2 Heading RMSEs with GPS data outage introduced (Run II)

measurement disturbances affecting the sensor devices. The GPS devices had different HDOP and Fix values during the two runs hence the difference in *GPSEC_yaw* heading values.

Table 1 gives the RMSE of the device measurements and derived step-by-step values with no GPS data outages. It can be seen that the proposed algorithm showed a slight improvement over all the GPS COG values while there was marked improvement over the EC value. It must be noted that the EC exhibited the biggest difference between the two runs with RMSE of 1.6551 and 10.5466.

GPS data outages were introduced to further check the performance

Table 2 RMSE with data outage introduced to all three GPS devices

	Run I	Run II
GPS#1/ #2/ #3 (COG)	6.6440, 4.0837, 5.7534	5.7781, 5.7489, 4.9902
Average of GPS COG	3.8335	3.6062
GPS only CnW	2.3695	2.0764
Electronic Compass	1.6551	10.5446
GPSEC_yaw CnW	0.5929	2.2598
EKF-CI (not use *GPSEC_yaw* for missing GPS Data)	4.7626	4.4975
EKF-CI (use *GPSEC_yaw* for missing GPS Data)	0.5258	1.2230

of the proposed method. The EC measurement, EKF result for each of the GPS with data outages, and final EKF-CI heading value are plotted with the Google Earth value as reference for each of the runs (Figs. 1 and 2).

The two plots are different from each other primarily due to the effect of the EC (RMSE of 1.6551 and 10.5446 for RUN I and II respectively) but applying the proposed algorithm gave a result whose RMSE is smaller compared than the individual/ average GPS COG and heading values as listed in Table 2. The effect and corresponding RMSE for each step of the proposed algorithm is also shown until the final heading value is arrived at.

Table 2 also shows that the resulting EKF-CI heading value has a higher RMSE when the process of substituting *GPSEC_yaw* into GPS_i_yaw when $GPS_i\_QUALITY = 0$ is disabled.

4. Conclusion

The necessity of utilizing inexpensive sensors such as Global Positioning Systems (GPS) and Electronic Compass (EC) with IMU to derive accurate heading data inspired this work. A novel procedure composed of our own plus several existing methods was formulated. The Forward Azimuth (FAz) method was utilized in calculating the heading based on the given GPS position data (*lat*, *long*). A Classification and Weighing method is then applied to the GPS data when combining them with the EC data (*GPSEC_yaw*). *GPSEC_yaw* is then substituted into any missing GPS missing data. The resulting data (*lat, long,* ψ) and covariance matrix will in turn be passed into an Extended Kalman Filter (EKF) process for fusion with IMU data. The GPS-IMU estimated means and covariances are then passed into a Covariance Intersection (CI) algorithm process to derive the overall fused heading value. A new covariance matrix is also generated by the CI which is utilized in the next EKF process as the current estimate of the error covariance. Actual GPS, EC and IMU data were recorded to evaluate each part of the proposed process. Experimental tests showed that there is improved overall heading value due to the positive interaction between successive sub-methods.

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