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AUTOMATIC IDENTIFICATION SYSTEM (AIS) DYNAMIC DATA ESTIMATION BASED ON DISCRETE KALMAN FILTER (KF) ALGORITHM

ABSTRACT

Due to the safety reason, the ship movement on the littoral area should be monitored, tracked, recorded and stored. Automatic Identification System (AIS) is the perfect tool to ensure this requirement. The limit probability for the AIS dynamic data availability can be limited by the lack of Global Position System (GPS) signal, heading (HDG) and rate of turn (ROT) data in position report. Availability of data link is an additional limitation. For this purpose, it is possible to attach the Discrete Kalman filter (KF) for the position, and course estimation. Coordinate estimation in the absence of a transmission link can improve the quality of AIS service at Vessel Traffic Service (VTS) stations. This article presents Kalman filtering algorithm to improve the possibilities of ship motion tracking and monitoring in the TSS (Traffic Separation Scheme) and fairways area. Only 39 iterations were presented to familiarize how the Kalman filter algorithm works. The archival data from 2006 were used deliberately. During that time, there were problems with the AIS availability service. With the use of measurements series from those years, it is easier to observe the effectiveness of Kalman filter in absence of AIS data.

Key words:
AIS, Kalman filter, AIS data estimation.

INTRODUCTION

At present, according to increased maritime transport, we pay particular attention to the safety aspect. The downsizing of crew forced the introduction of new

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technological solutions for safety navigation. It is possible to define the coordinates of your own ship. In relation to the other ships You must rely on navigation systems. One of the commonly used systems for this purpose is AIS. Unfortunately, AIS developers did not meet integrity, availability and reliability expectations. Therefore, appropriate steps must be taken to minimize the risk of unreliable information. Over the years, a number of articles have been published about AIS data integrity and availability. Looking for a solution to the reliability problem of navigation systems presented in [5, 7], it is proposed to use the discrete KF to estimate coordinates for AIS position reports.

STATE OF KNOWLEDGE ON THE DISCRETE KALMAN FILTER ALGORITHM

The Kalman filter estimates a process by using a form of feedback control: the filter estimates the process state at some time and then obtains feedback in the form of (noisy) measurements. The equations for the Kalman filter fall into two groups: time update equations and measurement update equations. The time update equations are responsible for projecting forward (in time) the current state and error covariance estimates to obtain the a priori estimates for the next time step. The measurement update equations are responsible for the feedback — i.e. for incorporating a new measurement into the a priori estimate to obtain an improved a posteriori estimate.

The time update equations can also be thought of as predictor equations, while the measurement update equations can be thought of as corrector equations. Indeed the final estimation algorithm resembles that of a predictor-corrector algorithm for solving numerical problems as shown below in figure 1 [11].

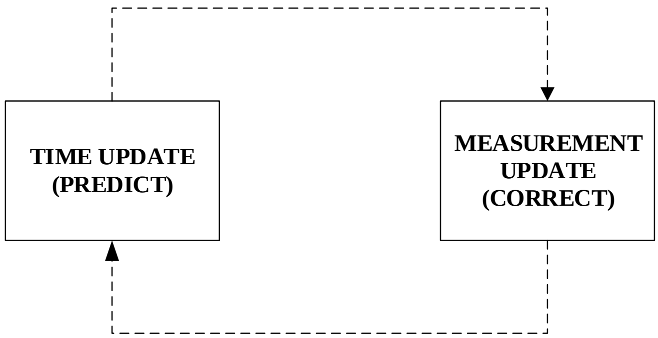

Fig. 1. The ongoing discrete Kalman filter cycle [11]

The equations for the time and measurement updates are presented below. According to formula (1), (2) discrete Kalman filter time update equations are:

$$\hat{x}_k^- = A \cdot \hat{x}_{k-1} + B \cdot u_k + w_{k-1}, \tag{1}$$

where:
$\hat{x}_k^-$ — estimated state vector;
A — transition matrix;
$\hat{x}_{k-1}$ — previous estimated state vector;
B — output matrix;
u_k — control variable vector;
w_{k-1} — previous state noise matrix

and

$$P_k^- = A \cdot P_{k-1} \cdot A^T + Q, \tag{2}$$

where:
P_k^- — process error covariance;
P_{k-1} — previous state process covariance;
A^T — transpose of a matrix;
Q — process noise covariance.

The state and covariance matrix estimates forward from time step *k-1* to step *k*.

According to formula (3), (4), (5), discrete Kalman filter measurement update equations are presented below:

$$K_k = P_k^- \cdot H^T \cdot (H \cdot P_k^- \cdot H^T + R)^{-1}, \tag{3}$$

where:
K_k — Kalman gain;
H^T — transpose of simply transformation matrix;
H — simply transformation matrix;
R — sensor noise covariance

and

$$\hat{x}_k = \hat{x}_k^- + K_k \cdot (z_k - H \cdot \hat{x}_k^-), \tag{4}$$

where:
$\hat{x}_k$ — a posteriori estimate of the state at step k;
$\hat{x}_k^-$ — a priori estimated state;
z_k — actual measurement vector

and

$$P_k = (I - K_k \cdot H) \cdot P_k^-, \tag{5}$$

where:
P_k — process error covariance matrix;
I — identity matrix;
P_k^- — process error covariance ahead.

1. The first task during the measurement update is to compute the Kalman gain K_k.
2. The next step is to actually measure the process to obtain z_k and then to generate an a posteriori state estimate by incorporating the measurement as in equation $\hat{x}_k$ (4). Again equation (4) $\hat{x}_k$ a posteriori state estimate as a linear combination of an a priori estimate $\hat{x}_k^-$ and a weighted difference between an actual measurement z_k and a measurement prediction $H \cdot \hat{x}_k^-$ [11].

The final step is to obtain an a posteriori error covariance estimate via equation (5). Figure 2 offers a complete picture of the operation of the filter [11].

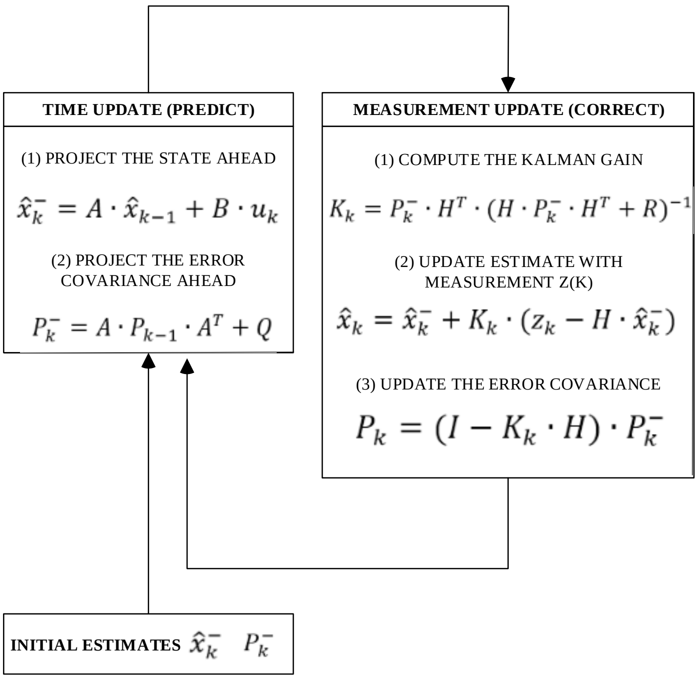

Fig. 2. A complete picture of the operation of the Kalman filter [11]

Because most of vessels navigating in TSS and fairways and by the shortest route we may assume that vessels navigating along linear path, Thus the first algorithm will use the linear movement description. The second algorithm will use Kalman filtering.

LINEAR ALGORITHM FOR SHIP MOVEMENT PREDICTION

According to technical specification [3] every vessels equipped with AIS receiver transmits position report about its movement. These selected data are presented in table 1.

Tab. 1. Selected data of AIS Position Report [3]

Parameter	Description
Message ID	Identifier for this Message 1, 2 or 3.
User ID	Unique identifier such as MMSI number.
Rate of turn	0 to +126 = turning right at up to 708° per min or higher; 0 to –126 = turning left at up to 708° per min or higher; Values between 0 and 708° per min coded by ROT AIS = 4.733 SQRT(ROT sensor) degrees per min where ROT sensor is the Rate of Turn as input by an external Rate of Turn Indicator (TI). ROT AIS is rounded to the nearest integer value. +127 = turning right at more than 5º per 30 s (No TI available); –127 = turning left at more than 5º per 30 s (No TI available); –128 (80 hex) indicates no turn information available (default). ROT data should not be derived from COG information.
Speed over ground	Speed over ground in 1/10 knot steps (0–102.2 knots) 1 023 = not available, 1 022 = 102.2 knots or higher.
Longitude	Longitude in 1/10 000 min (±180º, East = positive (as per 2's complement), West = negative (as per 2's complement). 181 = (6791AC0h) = not available = default).
Latitude	Latitude in 1/10 000 min (±90°, North = positive (as per 2's complement), South = negative (as per 2's complement). 91°(3412140h) = not available = default).
Course over ground	Course over ground in 1/10 = (0–3599). 3600 (E10h) = not available = default. 3 601-4 095 should not be used.
Time stamp	UTC second when the report was generated by the electronic position system (EPFS) (0–59, or 60 if time stamp is not available, which should also be the default value, or 61 if positioning system is in manual input mode, or 62 if electronic position fixing system operates in estimated (dead reckoning) mode, or 63 if the positioning system is inoperative).

If vessel is on the way, moored, at anchor, we know its speed over ground (V) in knots, course over ground (ψ), geographic position (φ, λ). For the research purpose ψ was converted to $\frac{m}{s}$ according to formula (10), and geographic position was converted to Cartesian coordinates (x, y) according to formula (6), (7), (8), (9) [2]. Finally, coordinates will be presented with the use a 2-dimensional Cartesian coordinate system — The Universal Transverse Mercator (UTM).

With the use of ellipsoid WGS-84 parameters, estimate the square of the first eccentric e^2 [1]

$$e^2 = \frac{a^2 - b^2}{a^2}, \tag{6}$$

where:
a — semi-major axis;
b — semi-minor axis

and

$$a = 6378137{,}0\ m;$$

$$b = 6356752{,}3\ m.$$

Determine the radius of curvature for the first vertical circle N [1]

$$N = \frac{a}{\sqrt{1 - e^2 sin^2\varphi}}, \tag{7}$$

where
φ — latitude.

Then, the Cartesian coordinates take the form [1]:

$$X = (N + h) \cdot cos\varphi \cdot cos\lambda; \tag{8}$$

$$Y = (N + h) \cdot cos\varphi \cdot sin\lambda; \tag{9}$$

$$Z = [N - (1 - e^2) + H], \tag{10}$$

where:
H — height of the point 'P';
λ — longitude.

According to formula (10), speed over ground given in [kt] should be converted to [m/s]

$$V' \left[\frac{m}{s}\right] = 0.514(4) \cdot V[\text{kt}], \tag{11}$$

where
V' — speed over ground in $[\frac{m}{s}]$

and

$$\omega' \left[\frac{\circ}{s}\right] = \frac{rot\left[\frac{\circ}{min}\right]}{60}, \tag{12}$$

where
ω' — rate of turn in $\left[\frac{\circ}{s}\right]$.

According to Δt = 10 s observations, AIS data were presented in table 2.

Tab. 2. AIS input data [own study]

observation number	**time [s]**	**Δt**	***X* [m]**	***Y* [m]**	**ψ [^{0}]**	**V' [m/s]**	**ω [$^0/_s$]**
0	0	0	6062445	4368335	3.8	5.2	0.13
1	11	11	6062500	4368343	5.1	5.2	0.12
2	20	9	6062556	4368351	6.3	5.2	–0.10
3	29	9	6062600	4368359	5.3	5.4	0.35
4	39	10	6062655	4368367	8.8	5.3	–0.12
5	50	11	6062711	4368375	7.6	5.5	–0.42
6	60	10	6062766	4368383	3.4	5.5	0.33
7	71	11	6062822	4368391	6.7	5.5	–0.29
10	99	28	6062988	4368422	3.8	5.3	0.50
11	110	11	6063043	4368430	8.8	5.4	–0.07
14	140	30	6063210	4368454	8.1	5.7	–0.08
15	149	9	6063254	4368462	7.3	5.6	–0.11
17	170	21	6063365	4368484	6.2	5.4	0.06
19	191	21	6063487	4368501	6.8	5.8	–0.28
20	200	9	6063542	4368509	4.0	5.4	0.47
31	311	111	6064152	4368604	8.7	5.9	–0.52
34	339	28	6064307	4368628	3.5	5.6	0.5
35	350	11	6064373	4368643	8.5	5.7	0.43
36	360	10	6064429	4368651	12.8	5.8	–0.28
38	379	19	6064540	4368667	10.0	5.9	–0.10

According to observation numbers and interval of recorded data, it is easy to observe the limitation of VHF data link availability and the latency of AIS position reports.

For the linear algorithm, coordinates might be estimated as follows:

$$X_k = X_{k-1} + \Delta X\,; \tag{13}$$

$$Y_k = Y_{k-1} + \Delta Y, \tag{14}$$

where:

X_{k-1}, Y_{k-1} — coordinates for the previous moment — AIS data;
$\Delta X, \Delta Y$ — shift coordinates in x and y axis.

If [4]

$$\Delta X = \frac{a_x \cdot \Delta t^2}{2}; \tag{15}$$

$$\Delta Y = \frac{a_y \cdot \Delta t^2}{2} \tag{16}$$

and [9]

$$a_x = \frac{V'_k \cdot \cos(\psi_k + \omega'_k \cdot \Delta t) - \cos(\psi_{k-1})}{\Delta t}; \tag{17}$$

$$a_y = \frac{V'_k \cdot \sin(\psi_k + \omega'_k \cdot \Delta t) - \sin(\psi_{k-1})}{\Delta t}, \quad (18)$$

where:

a_x, a_y — acceleration in *x* and *y* axis;

ω'_k — rate of turn;

V' — speed over ground;

ψ — course over ground.

DISCRETE KALMAN FILTERING ALGHORITM FOR SHIP MOVEMENT PREDCTION

The Kalman filter has been the subject of extensive research and application, particularly in the area of autonomous or assisted navigation. This is a recursive algorithm responsible for discrete linear dynamic process estimation. The algorithm is responsible for minimize the mean of the squared error. Due to the reason discrete KF might be applied for ship movement estimation [11].

For *k* iteration, and for 2 dimension model the state vector $\boldsymbol{X}_i$ is

$$\boldsymbol{X_i} = \begin{bmatrix} x_k \\ y_k \\ V'_k \cdot \cos(\psi_k) \\ V'_k \cdot \sin(\psi_k) \end{bmatrix}, \quad (19)$$

where:

x_k, y_k — UTM coordinates;

$V'_k \cdot \cos(\psi_k)$, $\psi'_k \cdot \sin(\psi_k)$ — linear speed in x and y axis.

For the initial state

$$\boldsymbol{X_0} = \begin{bmatrix} 0\,m \\ 0\,m \\ 0\,m/s \\ 0\,m/s \end{bmatrix}.$$

For the 1 iteration

$$\boldsymbol{X_1} = \begin{bmatrix} 6062445\,m \\ 4368335\,m \\ 5{,}2\,m/s \\ 0{,}3\,m/s \end{bmatrix}.$$

The transition matrix for 2 dimension model is presented according to formula [4]:

$$\boldsymbol{A} = \begin{bmatrix} 1 & 0 & \Delta t & 0 \\ 0 & 1 & 0 & \Delta t \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \tag{20}$$

where

Δt =10 s — interval between current and previous measurements.

To estimate predicted state matrix $\hat{x}_k^-$, the product of output matrix $\boldsymbol{B}$ and control variable vector $\boldsymbol{u_k}$ for 2 dimension model is presented as follow

$$\boldsymbol{B} \cdot \boldsymbol{u_k} = \begin{bmatrix} a_x \cdot \frac{\Delta t^2}{2}\ [m] \\ a_y \cdot \frac{\Delta t^2}{2}\ [m] \\ a_x \cdot \Delta t\ [m/s] \\ a_y \cdot \Delta t\ [m/s] \end{bmatrix}. \tag{21}$$

If there are no information about imperfection of measuring sensors for observed vessel via AIS, noise in the process vector w_{k-1} for the previous iteration is

$$\boldsymbol{w_{k-1}} = \begin{bmatrix} 0\ [m] \\ 0\ [m] \\ 0\ [m/s] \\ 0\ [m/s] \end{bmatrix},$$

then predicted state matrix $\hat{x}_k^-$ is

$$\boldsymbol{\hat{x}_k^-} = A \cdot \hat{x}_{k-1} + B \cdot u_k + w_{k-1}, \tag{22}$$

where

$\hat{x}_{k-1}$ — previous state vector.

To estimate previous state process covariance matrix P_{k-1}, following assumption were adopted for the first 5 iterations.

If

$$\sigma_x = 10\ m, \sigma_y = 10\ m, \sigma_x^V = 0.5\ \frac{m}{s}, \sigma_y^V = 0.5\ \frac{m}{s}$$

and if

$$P_{k-1} = \begin{bmatrix} {\sigma_x}^2 & cov(x,y) & cov(x,V_x) & cov(x,V_y) \\ cov(y,x) & {\sigma_y}^2 & cov(y,V_x) & cov(y,V_y) \\ cov(V_x,x) & cov(V_x,y) & {\sigma_x^V}^2 & cov(V_x,V_y) \\ cov(V_y,x) & cov(V_y,y) & cov(V_y,V_x) & {\sigma_y^V}^2 \end{bmatrix}, \tag{23}$$

then

$$P_{k-1} = \begin{bmatrix} 100\,m^2 & 100\,m^2 & 5\,m^2/s & 5\,m^2/s \\ 100\,m^2 & 100\,m^2 & 5\,m^2/s & 5\,m^2/s \\ 5\,m^2/s & 5\,m^2/s & 0.25\,m^2/s^2 & 0.25\,m^2/s^2 \\ 5\,m^2/s & 5\,m^2/s & 0.25\,m^2/s^2 & 0.25\,m^2/s^2 \end{bmatrix}.$$

For estimate previous state process covariance matrix P_{k-1}according to formula (23) for *k=5+i* iteration, elements of the P_{k-1} matrix are presented below [6]:

$$\sigma_x{}^2 = \Delta t^2 \cdot \left[(\sigma_V \cdot \cos(\psi_{k-1}))\right]^2 + \Delta t^2 \cdot \left[\sigma_\psi \cdot V_k \cdot \cos(\psi_k)\right]^2; \tag{24}$$

$$\sigma_y{}^2 = \Delta t^2 \cdot \left[(\sigma_V \cdot sin(\psi_{k-1}))\right]^2 + \Delta t^2 \cdot \left[\sigma_\psi \cdot V_k \cdot \cos(\psi_k)\right]^2; \tag{25}$$

$$\sigma_{Vx}{}^2 = \left[(\sigma_V \cdot cos(\psi_k))\right]^2 + \left[\sigma_\psi{}^2 \cdot V_k \cdot \sin(\psi_k)\right]^2; \tag{26}$$

$$\sigma_{Vy}{}^2 = \left[(\sigma_V \cdot sin(\psi_k))\right]^2 + \left[\sigma_{cog}{}^2 \cdot V_k \cdot \cos(\psi_k)\right]^2; \tag{27}$$

$$cov(x,y) = cov(y,x) = \tfrac{1}{2} \cdot \Delta t^2 \cdot \sin(2 \cdot \psi_k) \cdot \left[\sigma_V{}^2 - (\sigma_\psi \cdot V_k)\right]; \tag{28}$$

$$cov(x,V_x) = cov(V_x,x) = \Delta t \cdot cos(\psi_k)^2 \cdot \left[\sigma_V{}^2 - (\sigma_\psi \cdot V_k)^2\right]; \tag{29}$$

$$cov(y,V_y) = cov(V_y,y) = \Delta t \cdot sin(\psi_k)^2 \cdot \left[\sigma_V{}^2 + (\sigma_\psi \cdot V_k)^2\right]; \tag{30}$$

$$cov(V_x,V_y) = cov(V_x,V_y) = \tfrac{1}{2} \cdot sin(2 \cdot \psi_k) \cdot \left[\sigma_V{}^2 + (\sigma_\psi \cdot V_k)^2\right]; \tag{31}$$

$$cov(y,V_x) = cov(V_x,y) = \tfrac{1}{2} \cdot \Delta t \cdot \sin(2 \cdot \psi_k) \cdot \left[\sigma_V{}^2 - (\sigma_\psi \cdot V_k)^2\right]; \tag{32}$$

$$cov(x,V_y) = cov(V_y,x) = \tfrac{1}{2} \cdot \Delta t \cdot \sin(2 \cdot \psi_k) \cdot \left[\sigma_V{}^2 - (\sigma_\psi \cdot V_k)^2\right]. \tag{33}$$

If process noise covariance Q

$$Q \cong P_{k-1}, \tag{34}$$

then process error covariance P_k^- for 2 dimension model is calculated according to formula (2).

If simply transformation matrix H is presented as follow

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{35}$$

and sensor noise covariance matrix R is calculated in every iteration, where diagonal values are variances of last 5 measurements of coordinates and velocity

$$R = \begin{bmatrix} {\sigma_x}^2 & 0 & 0 & 0 \\ 0 & {\sigma_y}^2 & 0 & 0 \\ 0 & 0 & {\sigma_x^V}^2 & 0 \\ 0 & 0 & 0 & {\sigma_y^V}^2 \end{bmatrix}, \tag{36}$$

then Kalman gain K_k is calculated in every iteration according to formula (3).

If actual measurement vector z_k is presented as follow

$$z_k = \begin{bmatrix} x_k\ [m] \\ y_k\ [m] \\ V'_k \cdot \cos(\psi_k)\ [m/s] \\ V'_k \cdot \sin(\psi_k)\ [m/s] \end{bmatrix}, \tag{37}$$

then a posteriori estimate of the state at step k $\hat{x}_k$ is estimated according to formula (4).

Finally, if identity matrix takes form

$$I = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \tag{38}$$

then process error covariance matrix P_k is calculated according formula (5).

If coordinates are unavailable, then course over ground for k iteration is calculated according to formula [6]

$$\psi_k = atan\left(\frac{y_k - y_{k-1}}{x_k - x_{k-1}}\right) \tag{39}$$

and linear speed over ground in x and y axis is calculated according to formulas:

$$V_k^x = cos(\psi_k) \cdot V_k [m/s]; \tag{40}$$

$$V_k^y = sin(\psi_k) \cdot V_k [m/s]. \tag{41}$$

RESEARCH OUTCOMES

Measurement experiment has been conducted in area Gulf of Gdansk. The archival data from 2006 were used deliberately. Only 39 iterations with the use of Discrete Kalman Filtering Algorithm were carried out to reduce VHF AIS data link unavailability. The research outcomes of AIS and KF data fusion to improve availability of VHF AIS data link were presented in table 3.

Tab. 3. The research outcomes of AIS and KF data fusion

i	*t* [s]	*y* [m]	*x* [m]	$\psi_{est.}$ [°]	$\Delta\psi$ [°]	Δx [m]	Δy [m]	$M_{x,y}$ [m]	M_V [m/s]
0	0	4368335	6062445	3,8	0	0,0	0,0	14,1	0,7
1	10	4368339	6062497	8,3	−3,2	4,0	3,0	14,1	0,7
2	20	4368350	6062554	8,1	−1,8	1,0	2,0	14,1	0,7
3	30	4368355	6062607	10,3	−5	4,0	−7,0	10,5	0,5
4	40	4368362	6062659	8,3	0,5	5,0	−4,0	10,8	1
5	50	4368373	6062711	8,1	−0,5	2,0	0,0	10,8	1,1
6	60	4368382	6062766	8,3	−4,9	1,0	0,0	10,8	1,1
7	70	4368391	6062822	8,1	−1,4	0,0	0,0	10,8	1,1
8	80	4368399	6062876	8,1	−1,4			10,8	1,1
9	90	4368405	6062931	8,1	−1,4			10,8	1,1
10	100	4368420	6062988	8,1	−4,3	2,0	0,0	10,7	1,1
11	110	4368429	6063043	8,3	0,5	1,0	0,0	10,7	1,1
12	120	4368437	6063096	8,3	0,5			10,7	1,1
13	130	4368445	6063149	8,3	0,5			11,1	1,1
14	140	4368453	6063210	8,3	−0,2	1,0	0,0	11	1,1
15	150	4368462	6063254	10,3	−3	0,0	0,0	11	1,1
16	160	4368471	6063309	10,3	−3			10,7	1,1
17	170	4368483	6063365	10,3	−4,1	1,0	0,0	10,7	1,1
18	180	4368493	6063418	10,3	4,1			11,3	1,1
19	190	4368501	6063487	10,3	−3,5	0,0	0,0	10,7	1,1
20	200	4368510	6063542	8,3	−4,3	−1,0	0,0	10,7	1,1
21	210	4368518	6063595	8,3	4,3			10,7	1,1
22	220	4368522	6063650	8,3	4,3			10,7	1,1
23	230	4368526	6063703	8,3	4,3			10,7	1,1
24	240	4368534	6063756	8,3	4,3			10,7	1,1
25	250	4368541	6063810	8,3	4,3			10,7	1,1
26	260	4368549	6063863	8,3	4,3			10,7	1,1
27	270	4368557	6063917	8,3	4,3			10,7	1,1
28	280	4368565	6063970	8,3	4,3			10,7	1,1
29	290	4368573	6064023	8,3	4,3			10,7	1,1
30	300	4368579	6064076	8,3	4,3			10,7	1,1
31	310	4368597	6064152	8,3	0,4	7,0	0,0	10,7	1,1
32	320	4368607	6064210	8,3	0,4			11,4	1,1
33	330	4368617	6064268	8,3	0,4			11,4	1,1
34	340	4368627	6064307	8,3	−4,8	1,0	0,0	11,4	1,1
35	350	4368641	6064374	12,8	−4,3	2,0	−1,0	11	1,1
36	360	4368651	6064428	8,1	4,7	0,0	1,0	11,1	1,1
37	370	4368660	6064486	8,1	4,7			11,3	1,1
38	380	4368667	6064540	8,1	1,9	0,0	0,0	11,3	1,1

i — iteration number
x, y — UTM coordinates estimated with the use of KF algorithm
ψ_{est} — course over ground estimated with the use of KF algorithm coordinates
$\Delta x, \Delta y$ — difference between AIS and KF estimated coordinates
$\Delta\psi$ — difference between AIS and KF estimated course over ground
$M_{x,y}$ — mean error of coordinates
M_V — mean error of speed over ground

Dark grey lines on table 3 presents updated data with the use of discrete Kalman filtering algorithm. The use of the Kalman filter was intended to improve the availability of AIS dynamic information displayed on the Vessel Traffic Service (VTS) stations. The research outcomes for the discrete KF estimation for Cartesian Coordinates were presented on figure 3.

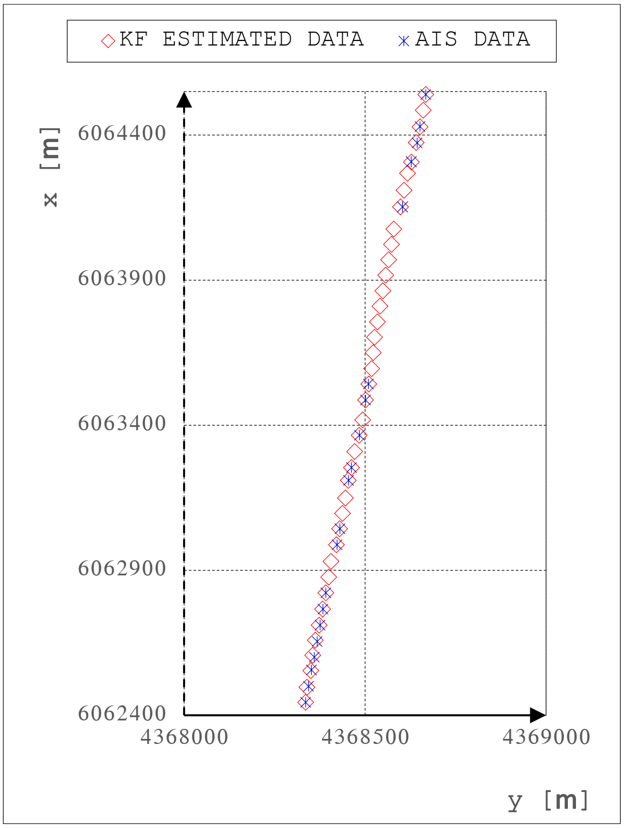

Fig. 3. UTM coordinates for the AIS data and estimated coordinates (UTM) with the use of discrete Kalman filtering algorithm [own study]

Estimated course over ground (*est.* ψ[°]) was calculated according the formula (39). The scores of course estimation were presented on table 3. The differences between AIS data course and KF estimated course were presented on figure 4. The course differences did not exceed 5 degrees. The outcomes repeatability for the iteration number 21-30 is the result of the data generated by the Kalman filter algorithm.

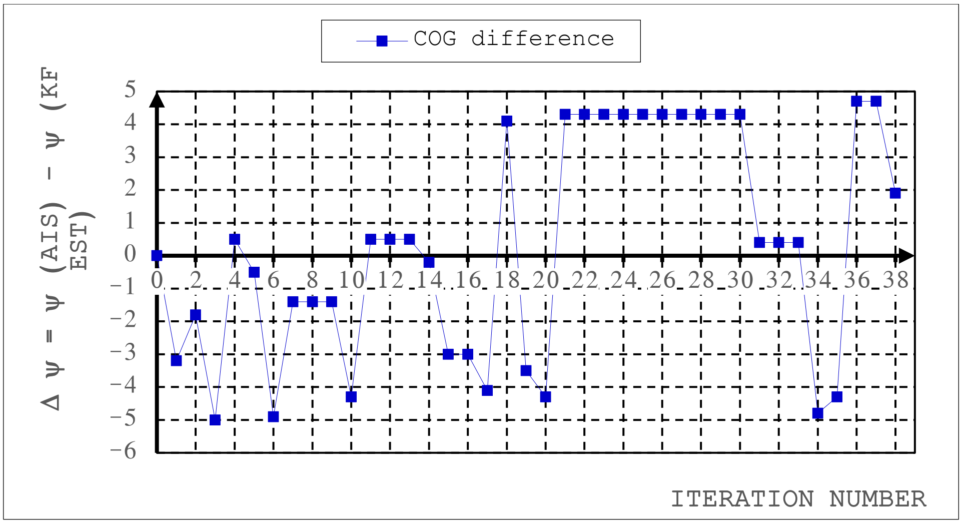

Fig. 4. The difference between AIS course over ground and estimated course over ground with the use of discrete Kalman filtering algorithm [own study]

Coordinate differences for the x and y direction with the maximum 7 m difference were presented on figure 5. According to the research scores, maximum differences were typical for the first five iterations, where KF algorithm did not work and after AIS signal appearance, for 31 iteration.

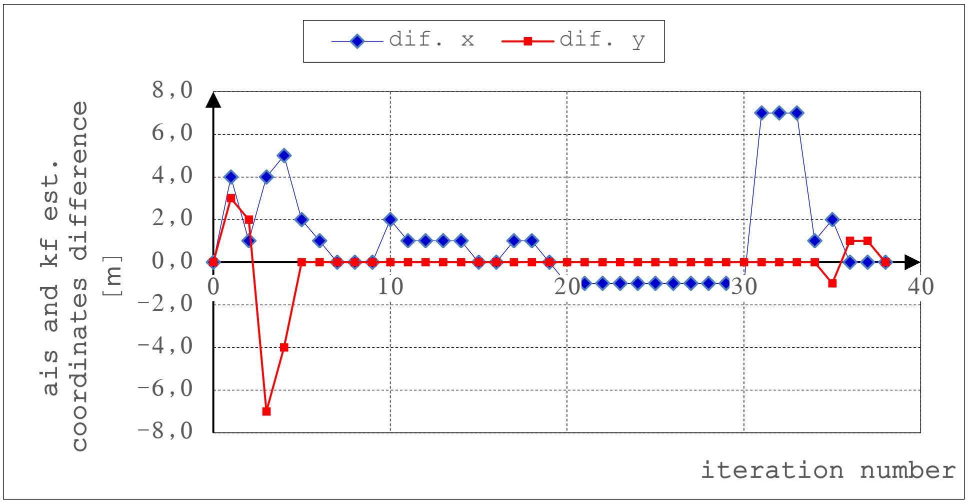

Fig. 5. Differences between AIS and KF estimated (x, y) coordinates [own study]

Similar proportion can be observed for mean error of coordinates calculation according to formula

$$M_{xy} = \sqrt{\sigma_x^2 + \sigma_y^2}. \tag{42}$$

An outcome scores for the mean error of coordinates were presented on figure 6.

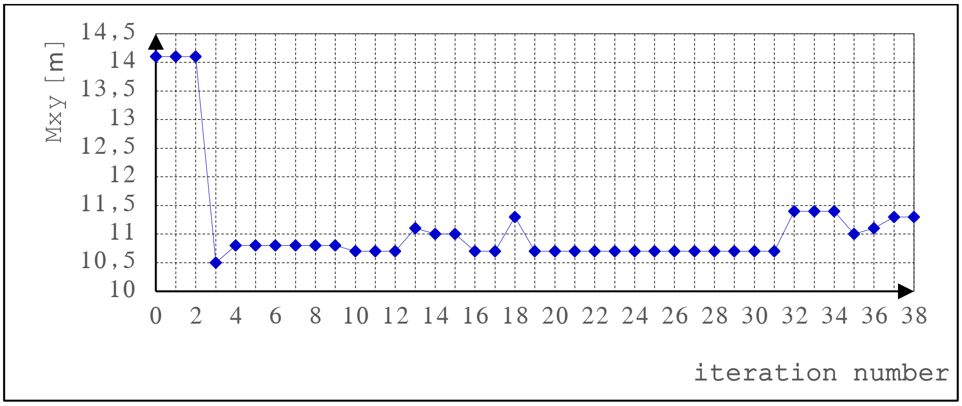

Fig. 6. Mean error of estimated coordinates [own study]

An opposite outcome scores for the mean error of speed over ground were presented on figure 7 and calculated according the formula

$$M_V = \sqrt{\sigma_{Vx}{}^2 + \sigma_{Vy}{}^2}. \tag{43}$$

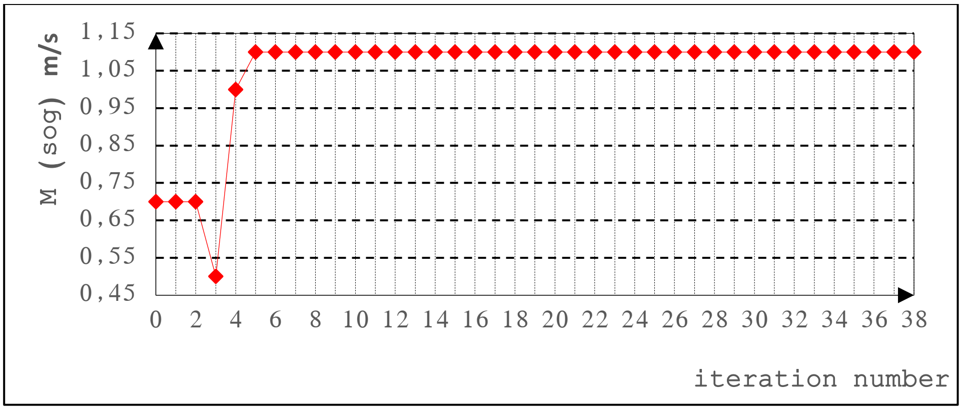

Fig. 7. Mean error of estimated speed over ground [own study]

CONCLUSION

Discrete Kalman filter algorithm seems to be a good tool for update position in case of AIS dynamic data unavailability. Only 39 iterations were presented to demonstrate the principle of discrete Kalman Filter. According to investigation scores, Kalman Filter application decrease the mean error of coordinates up to 10 meters. The essential factor affecting the correct Kalman filter operation is the appropriate estimation of the sensor noise covariance matrix R and process noise covariance Q. In the research studies, registered AIS position reports (from 2006) were used. Position reports were collected in area of VTS ZATOKA. An incomplete archive position reports has been selected deliberately to set the purpose of use Discrete Kalman Filter algorithm. Kalman Filter algorithm did not work for the first 5 iteration. This is easily noticeable for the estimated errors, for individual iterations.

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ESTYMACJA DANYCH DYNAMICZNYCH AUTOMATYCZNEGO SYSTEMU IDENTYFIKACJI (AIS) W OPARCIU O ALGORYTM DYSKRETNEGO FILTRU KALMANA (KF)

STRESZCZENIE

Dla zapewnienia bezpieczeństwa żeglugi ruch jednostek pływających w rejonie wód wewnętrznych i w strefie przybrzeżnej powinien być monitorowany i rejestrowany, najlepiej w postaci cyfrowej. Doskonałym narzędziem do tego celu jest automatyczny system identyfikacji (AIS). Dostępność danych dynamicznych AIS może zostać jednak zredukowana z powodu braku dostępu do systemów pozycjonowania (GPS) oraz braku danych o kursie (HDG) i prędkości kątowej (ROT) w raportach pozycyjnych. Niedostępność łącza komunikacyjnego w paśmie VHF jest dodatkowym ograniczeniem systemu. W celu estymacji danych dotyczących pozycji i kursu statku w czasie, gdy dane te nie są dostępne, można zastosować dyskretny filtr Kalmana (KF). Estymacja współrzędnych w przypadku braku łącza komunikacyjnego wynikającego z ograniczeń dostępności systemu AIS podnosi jakość serwisu zarządzania ruchem statków (VTS). W artykule zaprezentowano 39 iteracji filtru Kalmana. Celowo zastosowano dane archiwalne z 2006 roku, albowiem w tych rejestracjach występują wyraźne przerwy w strumieniu danych. Rzecz w tym, że efektywność zaproponowanego rozwiązania łatwiej zaobserwować, jeśli zostaną zastosowane serie pomiarowe z okresu, gdy występowały problemy z dostępnością serwisu AIS.

Słowa kluczowe:
AIS, filtr Kalmana, estymacja danych AIS.