POLISH MARITIME RESEARCH 4(76) 2012 Vol 19; pp. 78-85
10.2478/v10012-012-0043-1

Data fusion in a navigational decision support system on a sea-going vessel

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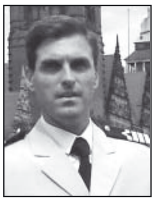
ABSTRACT



The problem of data fusion in a navigational decision support system on a sea-going vessel has been analyzed. The computing algorithm herein applied for solving the formulated problem is based on a multi-sensor Kalman filter. On the practical side, results of the tests done in real conditions are shown. The tests conducted onboard m/s Nawigator XXI, have been aimed at the verification of the proposed computing algorithm implemented in a prototype navigational decision support system.

Key words: data fusion; navigational decision support system; multi-sensor Kalman filter

INTRODUCTION

In the literature on the problems of information processing the terms data integration and data fusion are very often used as synonyms [9]. This author assumes that the term data integration is understood as a process in which data from various, generally physically separate sources are combined into a consistent and readable whole in a manner allowing to obtain new, more comprehensive information that would be impossible to get from each individual source. Data fusion, on the other hand, is understood as a process of merging data from various sources, however, describing the same quantity. Therefore, this process results in obtaining more reliable and more accurate information.

Data fusion algorithms are naturally applied when input data needed to solve a specific problem are simultaneously obtained from many redundant measurement devices. For further overall processing these data have to be transformed into one signal, which will take account for the information from all sensors. Thus obtained data should be more precise than those derived individually from one source. Besides, this approach increases the level of safety of system which may be affected by a possible lack of input data. Even if one source (device) fails the others guarantee effective operation. This observation is of particular importance in real time systems.

Methods and algorithms of data fusion find applications in many problems across various scientific disciplines, e.g. in medicine [7], land transport [14], processes of knowledge retrieval from data bases [17], problems of mobile agents [18], satellite image integration [11]. In this article data fusion is used for solving problems of dynamic object (vessel) positioning in marine navigation.

Chapter V, paragraph 19 of the SOLAS (Safety Of Life At Sea) Convention [5] deals with mandatory fitting of sea-going ships with navigational systems and equipment. Which equipment items a ship should carry depends on the date the ship's building commenced (laying the keel) and on its gross tonnage. According to the above mentioned document, ships with a tonnage above 500 GT (majority of sea-going vessels) whose construction started after 01 July 2002 should be equipped with, but not limited to:

- Global Navigation Satellite System (GNSS) receiver, determining ship's position (latitude and longitude) automatically,
- AIS system (Universal Shipborne Automatic Identification System), providing, *inter alia*, information on own ship's position (latitude and longitude).

Practice has shown that most sea-going vessels comply with the above requirements as they have redundant equipment. This is an effect of continually reduced costs of GNSS receivers due to growing demand for satellite navigation systems in land transport.

No wonder, modern ships have several different devices with sensors measuring their own position (latitude and longitude). The navigator, having differing data on his ship's position, may face difficulties in making the right decision. On the other hand, relying exclusively on measurements from one device is a risky solution as the information source may fail. Therefore, it seems purposeful to apply the process of navigational data fusion. One of the methods to solve this problem is application of a multi-sensor Kalman filter [1, 15,16].

ALGORITHM OF NAVIGATIONAL DATA FUSION WITHIN THE KALMAN FILTER

To meet the demands of the herein considered algorithm of navigational data fusion, we introduce the following mathematical model of discrete stochastic system with l sensors [2,3,4]:

$$
\begin{aligned}
\mathbf{x}(t+1) &= \mathbf{\Phi}\cdot\mathbf{x}(t)+\mathbf{w}(t) \\
\mathbf{y}_i(t) &= \mathbf{H}_i\cdot\mathbf{x}(t)+\mathbf{v}_i(t) \quad i=1,2,\ldots,l
\end{aligned}
\tag{1}
$$

where:

$\mathbf{x}(t)=\begin{bmatrix} x(t) \\ y(t) \\ v_x(t) \\ v_y(t) \end{bmatrix} \in R^4$ – state vector at instant t,

(x(t), y(t)) – Cartesian coordinates of vessel position at instant t,

$(v_x(t), v_y(t))$ – vector of vessel velocity in the reference system at instant t,

$y_i(t) \in R^2$ – measurement vector of *i*-th sensor (Cartesian coordinates of vessel position from a GNSS receiver, vessel velocity vector from a Doppler log) at instant t,

$\Phi = \begin{bmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$ – constant system matrix,

$\mathbf{H}_i$ – constant matrix of i-th sensor (GNSS receiver: $\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$, Doppler log: $\begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$),

$\mathbf{w}(t)$, $\mathbf{v}_i(t)$ – vectors of disturbances with characteristics of white Gaussian noise with zero expected values and covariance matrices $\mathbf{Q}$ and $\mathbf{R}_i$, respectively, at instant t.

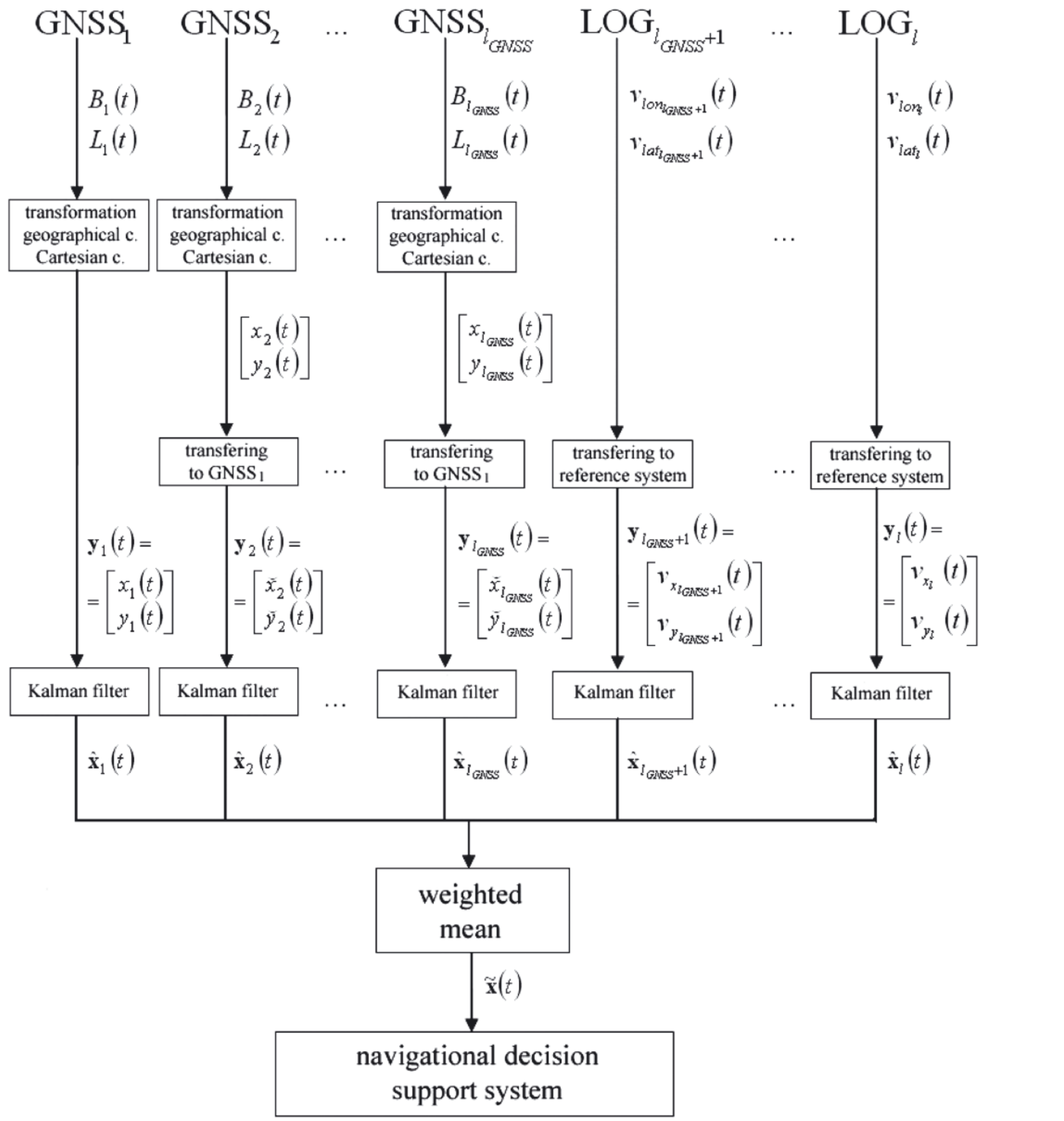


Fig. 1. A general diagram of the proposed navigational data fusion algorithm

A general diagram of navigational data fusion algorithm within the Kalman filter is shown in Fig. 1.

Denotations of the quantities included in Fig. 1:

l_{GNSS} – number of GNSS receivers ($1 \le l_{GNSS} \le l$),

$B_i(t)$, $L_i(t)$ – latitude and longitude of the vessel obtained by i-th GNSS receiver at instant t ($1 \le i \le l_{GNSS}$) [°],

$v_{lon_i}(t)$, $v_{lon_i}(t)$ – longitudinal and transverse velocities of the vessel obtained by i-th Doppler log at instant t ($l_{GNSS} + 1 \le i \le l$) [m/s],

$(\breve{x}_i(t), \breve{y}_i(t))$ – results of measurement of the Cartesian coordinates of the vessel, obtained by i-th GNSS receiver at instant t and transferred to the position of the first GNSS receiver ($2 \le i \le l_{GNSS}$) [m],

$v_{x_i}(t)$, $v_{y_i}(t)$ – results of measurement of vessel velocity vector obtained by i-th Doppler log at instant t ($l_{GNSS} + 1 \le i \le l$) [m/s],

$\hat{\mathbf{x}}_i(t)$ – estimates of state vector obtained through Kalman filtration for i-th subsystem,

$\widetilde{\mathbf{x}}(t)$ – vector of state estimates fusion.

The following navigational systems and equipment are sources of input data for the algorithm, where they undergo the fusion process:

- satellite navigation system receivers and the AIS system which carry out measurements of own vessel's position (latitude and longitude), represented as GNSS receivers in Fig. 1,
- Doppler logs, which provide measurements of longitudinal and transverse velocity components of own vessel.

For the effective operating of the algorithm the vessel must carry at least two of the mentioned devices. Additionally, a gyrocompass allowing to measure own vessel's heading needed in the process of internal data transformations, is required.

The circulation of signals in the proposed algorithm (Fig. 1) will be further described in detail.

Transformation of geographical coordinates into Cartesian coordinates

Results of measurements of own vessel position delivered by GNSS receivers have a form of geographical coordinates (Fig. 2), so that they cannot be directly used in the model (1). To transform them into the Cartesian coordinates the Gauss-Krüger projection was applied [6]. Then the relevant transformation formulas obtain the following form:

$$
\begin{aligned}
x(t) = {} & N(t)\cdot\cos(B(t))\cdot\Delta L(t) + \\
& + \frac{1}{6}\cdot N(t)\cdot\cos^3(B(t))\cdot(1 - T^2(t) + \eta^2(t))\cdot(\Delta L(t))^3 + \\
& + \frac{1}{120}\cdot N(t)\cdot\cos^5(B(t))\cdot(5 - 18\cdot T^2(t) + T^4(t) + 14\cdot\eta^2(t) - 58\cdot T^2(t)\cdot\eta^2(t))\cdot(\Delta L(t))^5 + \\
& + \frac{1}{5040}\cdot N(t)\cdot\cos^7(B(t))\cdot(61 - 479\cdot T^2(t) + 179\cdot T^4(t) - T^6(t))\cdot(\Delta L(t))^7 \\
y(t) = {} & S(t) + \frac{1}{2}\cdot N(t)\cdot\cos^2(B(t))\cdot(\Delta L(t))^2 + \\
& + \frac{T(t)}{24}\cdot N(t)\cdot\cos^4(B(t))\cdot(5 - T^2(t) + 9\cdot\eta^2(t) + 4\cdot\eta^4(t))\cdot(\Delta L(t))^4 + \\
& + \frac{T(t)}{720}\cdot N(t)\cdot\cos^6(B(t))\cdot(61 - 58\cdot T^2(t) + T^4(t) + 270\cdot\eta^2(t) - 330\cdot T^2(t)\cdot\eta^2(t))\cdot(\Delta L(t))^6 + \\
& + \frac{T(t)}{40320}\cdot N(t)\cdot\cos^8(B(t))\cdot(1385 - 3111\cdot T^2(t) + 543\cdot T^4(t) - T^6(t))\cdot(\Delta L(t))^8
\end{aligned}
\tag{2}
$$

where:

$N(t) = \dfrac{a^2}{b\cdot\sqrt{1+\eta^2(t)}}$ – radius of the first vertical curvature (for WGS 84 ellipsoid we can assume: a = 6378137 [m], b = 6356752.3141 [m]),

$\eta^2(t) = \dfrac{a^2 - b^2}{b^2}\cdot\cos^2(B(t))$ – non-dimensional auxiliary variable,

$\Delta L(t) = L(t) - L_0$ – difference between measurement results of a given longitude and the longitude of the axial meridian of the examined area (for the Szczecin area we can assume $L_0 = 0.2618$ [rad]),

$T(t) = tg(B(t))$ – non-dimensional auxiliary variable,

$S(t)$ – length of meridian arc B(t) [m].

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12:38:23 $GPRMC,103817,A,5358.580,N,01423.174,E,010.2,249.4,030909,002.1,E*72
12:38:24 $GPRMC,103818,A,5358.579,N,01423.169,E,010.2,249.6,030909,002.1,E*75
12:38:25 $GPRMC,103819,A,5358.578,N,01423.165,E,010.2,249.6,030909,002.1,E*79
12:38:26 $GPRMC,103820,A,5358.577,N,01423.160,E,010.2,249.6,030909,002.1,E*79
12:38:27 $GPRMC,103821,A,5358.576,N,01423.156,E,010.2,249.4,030909,002.1,E*7E
12:38:28 $GPRMC,103822,A,5358.575,N,01423.151,E,010.2,249.5,030909,002.1,E*78
12:38:29 $GPRMC,103823,A,5358.574,N,01423.147,E,010.3,249.4,030909,002.1,E*7F
12:38:30 $GPRMC,103824,A,5358.573,N,01423.142,E,010.3,249.3,030909,002.1,E*7D
12:38:31 $GPRMC,103825,A,5358.572,N,01423.138,E,010.2,249.4,030909,002.1,E*76
12:38:32 $GPRMC,103826,A,5358.571,N,01423.133,E,010.2,249.5,030909,002.1,E*7C
12:38:33 $GPRMC,103827,A,5358.570,N,01423.129,E,010.2,249.7,030909,002.1,E*75
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Fig. 2. Data from a GNSS receiver

The meridian arc length B(t) is found from the following formula:

$$\begin{aligned} S(t) = 6367449 \cdot B(t) + \\ - 16038.50874 \cdot \sin(2 \cdot B(t)) + \\ + \sin(4 \cdot B(t)) - 0.022198 \cdot \sin(6 \cdot B(t)) + \\ + 0.00003 \cdot \sin(8 \cdot B(t)) \end{aligned} \tag{3}$$

The proposed transformation reproduces accurately only measurements close to the axial meridian. The difference in the transformed length grows when it is further from the axial meridian, reaching a maximum at the edge of the zone (for a six-degree zone it equals 67 cm per 1 km of length). The area subject to navigational situation analysis to which the data from the fusion process will apply, should not exceed a circle with the radius of 10 nautical miles. If we take this into account and the fact that the selected axial meridian has to cross the analyzed area we can assume that transformation errors are minor and will not affect the quality of the fusion.

Transferring the measurement results from GNSS receivers to one common point

Aerials of GNSS receivers installed on board a ship are generally mounted in different places. As the aerials are some distance apart, the obtained measurement results should be brought, after passing through the block of transformation from geographical coordinates to Cartesian coordinates, to one common place to be subjected to the fusion process. This is due to the fact that in the model (1) the vessel position is understood as a specific material point. Most often it is interpreted as the hull centre of gravity. Unfortunately, it rarely happens that any of the aerials is placed exactly at such point, and the process of bringing the measurement results to a specific point is always burdened with an error (this is due to the need of using, in the process, the gyrocompass heading which is a measured quantity burdened this way with an error). Therefore, it is decided that in the proposed algorithm the place to which all measurement results are transferred is the position of one GNSS receiver aerial, preferably that of the most accurate receiver (if there is such). In this approach measurement results from one GNSS receiver ($GNSS_1$) will be free from additional deformations caused by the geometrical transformation. This transformation consists in combining the rotation by the angle (course) and the translation by the vector according to the following equations:

$$\begin{aligned} \breve{x}(t) &= x(t) + w_x \cos(\psi(t)) - w_y \sin(\psi(t)) \\ \breve{y}(t) &= y(t) + w_y \cos(\psi(t)) + w_x \sin(\psi(t)) \end{aligned} \tag{4}$$

where:
$\mathbf{w} = [w_x, w_y]$ – vector which specifies the position of a GNSS aerial relative to the $GNSS_1$ receiver aerial (Fig. 3) [m],
ψ – gyrocompass heading [rad].

Shifting the measurement results obtained from GNSS receivers will increase the measurement error by the value:

$$2\sqrt{w_x^{\,2} + w_y^{\,2}} \cdot \sin\left(\frac{e_{gyro}}{2} \right) \tag{5}$$

where:
e_{gyro} – gyrocompass error [rad].

As the gyrocompass error should not exceed 0.009 rad, while the distance between the GNSS aerials should not exceed 15 m, we can assume that errors caused by bringing the measurement results to one common location are negligibly small and will not affect the fusion quality.

Transferring the velocity measurement results to the reference system

In parallel with position measurement transformations, similar operations concerning velocity (over ground) measurements should be performed by using Doppler logs. Measurements of longitudinal and transverse velocity components of a vessel should be related to the introduced reference system through a rotation by the gyrocompass heading in accordance with to the following equations:

$$\begin{aligned} v_x(t) &= v_{lon} \cos(\psi(t)) - v_{lat} \sin(\psi(t)) \\ v_y(t) &= v_{lat} \cos(\psi(t)) + v_{lon} \sin(\psi(t)) \end{aligned} \tag{6}$$

The transformation will increase the measurement error by the value:

$$2\sqrt{v_{lon}^{\,2} + v_{lat}^{\,2}} \cdot \sin\left(\frac{e_{gyro}}{2} \right) \tag{7}$$

Since the gyrocompass error should not exceed 0.009 rad and the vessel speed should not be higher than 15 m/s, we can assume that errors caused by bringing velocity measurements to the reference system are also negligibly small and will not affect the fusion quality.

The Kalman filter

Estimates of the state vector $\hat{\mathbf{x}}_i(t)$ for *i*-th subsystem (relating to a sensor) are obtained by using a Kalman filter [8] for the model (1):

$$\begin{aligned} \hat{\mathbf{x}}_i(t \backslash t-1) &= \mathbf{\Phi} \cdot \hat{\mathbf{x}}_i(t-1 \backslash t-1) \\ \mathbf{E}_i(t) &= \mathbf{y}_i(t) - \mathbf{H}_i \cdot \hat{\mathbf{x}}_i(t \backslash t-1) \\ \mathbf{P}_i(t \backslash t-1) &= \mathbf{\Phi} \cdot \mathbf{P}_i(t-1 \backslash t-1) \cdot \mathbf{\Phi}^T + \mathbf{Q} \\ \mathbf{K}_i(t) &= \mathbf{P}_i(t \backslash t-1) \cdot \mathbf{H}_i^T \cdot \left[\mathbf{H}_i \cdot \mathbf{P}_i(t \backslash t-1) \cdot \mathbf{H}_i^T + \mathbf{R}_i \right]^{-1} \\ \mathbf{P}_i(t \backslash t) &= \mathbf{P}_i(t \backslash t-1) - \mathbf{K}_i(t) \cdot \mathbf{H}_i \cdot \mathbf{P}_i(t \backslash t-1) \\ \hat{\mathbf{x}}_i(t \backslash t) &= \hat{\mathbf{x}}_i(t \backslash t-1) + \mathbf{K}_i(t) \cdot \mathbf{E}_i(t) \end{aligned} \tag{8}$$

where:
$\mathbf{E}_i(t)$ – vector of innovation at instant t,
$\mathbf{K}_i(t)$ – filter gain matrix at instant t,
$\mathbf{P}_i(t \backslash t-1)$ – filtration errors covariance matrix determined without the knowledge of filter gain at instant t,
$\mathbf{P}_i(t \backslash t)$ – updated filtration errors covariance matrix,
$\hat{\mathbf{x}}_i(t \backslash t-1)$ – estimate of the state vector determined without the knowledge of measurements at instant t,
$\hat{\mathbf{x}}_i(t \backslash t)$ – updated estimate of the state vector.

Data fusion

The fusion of a set of data obtained from l sensors is expressed as a weighted mean:

$$\tilde{\mathbf{x}}(t) = \mathbf{A}_1(t) \cdot \hat{\mathbf{x}}_1(t) + \mathbf{A}_2(t) \cdot \hat{\mathbf{x}}_2(t) + K + \mathbf{A}_l(t) \cdot \hat{\mathbf{x}}_l(t) \tag{9}$$

where:
$\mathbf{A}_i(t)$ – weight matrices.

The weight matrices are derived from the formula:

$$\mathbf{A}_i(t) = \left[\sum_{j=1}^{l} \mathbf{P}_{jj}^{-1}(t) \right]^{-1} \cdot \mathbf{P}_{ii}^{-1}(t) \tag{10}$$

where:

$\mathbf{P}_{ij}(t)$ – matrix of cross covariance of error filtration between i-th and j-th subsystem of model (1).

Matrices of the cross covariance of filtration errors are determined from the following formula:

$$\mathbf{P}_{ij}(t) = [\mathbf{I}_4 - \mathbf{K}_i(t)\cdot\mathbf{H}_i]\cdot[\mathbf{\Phi}\cdot\mathbf{P}_{ij}(t-1)\cdot\mathbf{\Phi}^T + \mathbf{Q}]\cdot \cdot[\mathbf{I}_4 - \mathbf{K}_j(t)\cdot\mathbf{H}_j]^T \tag{11}$$

where:

$\mathbf{I}_4$ – 4 x 4 unit matrix.

The proposed approach is optimal as it minimizes the trace of error variance matrix of the fusion estimator [15, 16].

It should be emphasized that due to the used model (1), the algorithm of navigational data fusion is a positioning algorithm for rectilinear movement. That is why the fusion process cannot be continued when the vessel starts turning.

DATA FUSION IN THE NAVIGATIONAL DECISION SUPPORT SYSTEM

Rapid advancements in information technologies we have been witnessing in recent years, significantly affect the organization and execution of maritime transport processes. More attention is being paid to the construction of intelligent systems which utilize a wide range of telecommunication, computer, automation and measurement technologies, in order to protect traffic participants, increase effectiveness of the maritime transport system and protect natural environment resources. Intelligent transport systems (ITS) [12] are advanced applications with a capability of safer and better coordinated use of transport networks. One example of such applications is the Vessel Traffic Monitoring and Information System (VTMIS) presently being developed within the EU. The VTMIS consists of several components: the Vessel Traffic Service (VTS), Automatic Identification System (AIS), Ship Reporting System (SRS), Maritime Assistance Services (MAS), Long Range Identification and Tracking System (LRITS), computer-aided system of information exchange (SafeSeaNet).

In December 2005 the International Maritime Organization (IMO) started working on developing and implementing a new navigational strategy - e-navigation [10]. E-navigation is understood as gathering, integration, transmission, management and presentation of navigational information by means of electronic formats for the navigational support of port-to-port operations. The concept of e-navigation goes in line with the concept of maritime intelligent transport systems.

The development of navigational equipment and systems installed on sea-going ships created a demand for data integration and devising methods of navigational data presentation which would facilitate the navigator in decision making. Another stage consists in building specialized information systems assisting decision processes on the ship, such as pilotage and docking systems. Their development proceeds towards decision support systems which in turn have such functions as current situation analysis and generation of proposed solutions to dangerous (i.e.collision) situations.

The research team at the Institute of Marine Navigation, Maritime University of Szczecin, has developed a prototype navigation decision support in open sea areas, thus making a contribution toward the global work on intelligent systems and meeting today's demands of the maritime industry [13]. The computer-based system (hardware and software) can be easily installed on board a ship and work in real time. The prototype has the following functions:

- recording and decoding navigational data,
- navigational data integration,
- navigational data fusion,
- identification of a navigational situation,
- analysis and assessment of a navigational situation,
- generating anti-collision manoeuvre,
- prediction of a navigational situation,
- presentation of the processed information.

One of the functions is the process of navigational data fusion. In the prototype system this process is based on the implemented algorithm such as that presented in the previous chapter. The use of the computing algorithm ensures a number of advantages:

- increased reliability of the system,
- reduction of measurement errors,
- continuity of the system operation,
- data acquisition at greater frequency.

THE RESULTS OF FIELD TESTS

The algorithm of navigational data fusion implemented in the navigational decision support system was verified in real conditions on board the m/s *Nawigator XXI*. The field tests were carried out in the area of the Szczecin-Świnoujście fairway at the southwest Baltic Sea. During the tests the ship had the following navigational equipment and systems essential for the algorithm verification:

- AIS system - Nauticast X-Pack DS,
- GNSS receiver - CSI MiniMax,
- GNSS receiver - Koden KGP-913D,
- GNSS receiver - Trimble NT 200D,
- gyrocompass - Gyro STD22 Anschutz.

For technical reasons the input data for the tested algorithm were signals from two GNSS receivers (MiniMax, Koden) and the gyrocompass. The MiniMax was chosen as the primary GNSS receiver ($GNSS_1$) due to its higher accuracy.

The disturbance covariance matrix was assumed as:

$$\mathbf{Q} = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \tag{12}$$

while the sensor-related data (accounting for the characteristics of measuring devices) were assumed as:

$$\mathbf{R}_1 = \begin{bmatrix} 0.25 & 0 \\ 0 & 0.25 \end{bmatrix},\ \mathbf{w}_1 = [0 \quad 0]$$
$$\mathbf{R}_2 = \begin{bmatrix} 2.25 & 0 \\ 0 & 2.25 \end{bmatrix},\ \mathbf{w}_2 = [0.56 \quad -1.04] \tag{13}$$

These are the initial matrices of filtration error covariance and matrices of cross covariance of filtration errors (applied after each filter cancellation – subsequent start-up of the algorithm):

$$\mathbf{P} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0.0625 & 0 \\ 0 & 0 & 0 & 0.0625 \end{bmatrix} \tag{14}$$

First measurements from each device were assumed as the remaining initial values.

Fig. 4 and 5 present example records of ship positions measured when the ship proceeded along a straight track section. It can be seen that the measurements from the two GNSS receivers do not form a straight line, while the fusion of these measurements approximately makes up a straight line. This proves that the tested algorithm incorporating the signals from $GNSS_1$ and $GNSS_2$ receivers, performs correctly.

Fig. 6, in turn, illustrates a situation when measurement data from the $GNSS_1$ receiver (more accurate) form a straight line, but there occurs a period when the signal fades away. The fusion signal, however, is maintained thanks to signals from the other, $GNSS_2$ receiver. This is important from the viewpoint of the navigational decision support system, as fading may destabilize the system.

Fig. 7 presents a situation when the ship was not moving, lying at anchor. Also in this case for the navigational decision

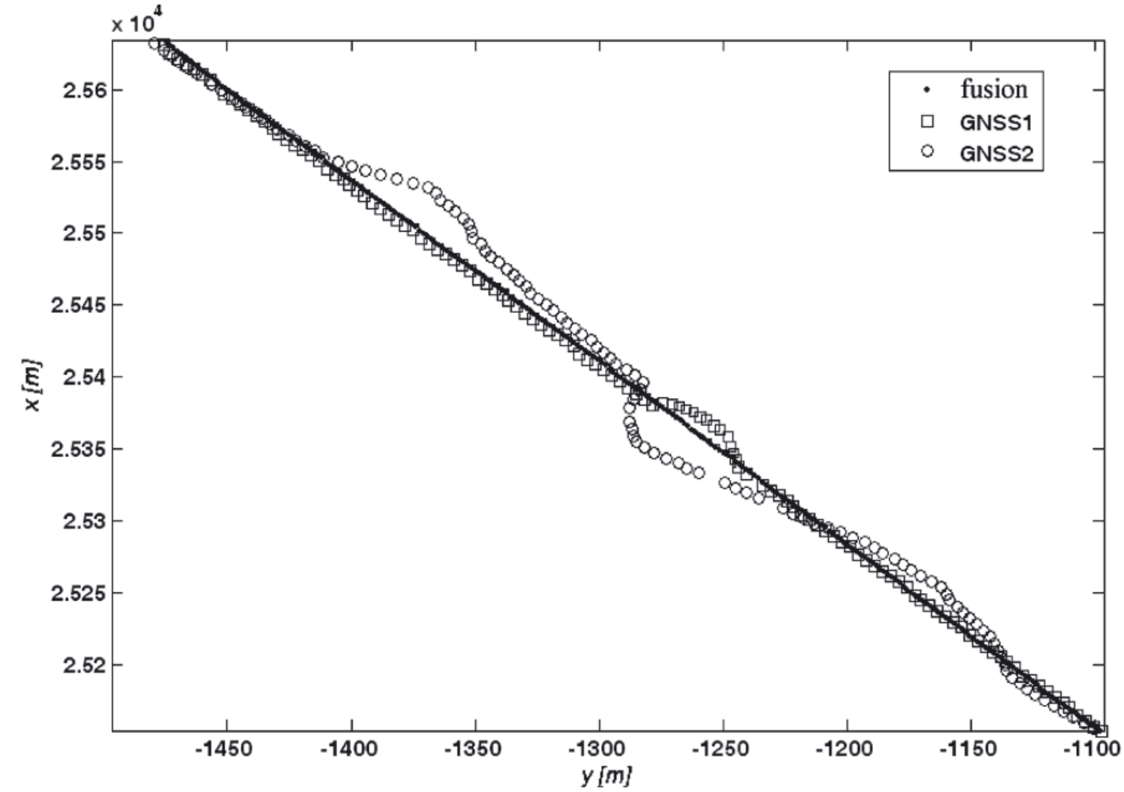

Fig. 4. *Ship's positions measured by $GNSS_1$ and $GNSS_2$ receivers and the measurement fusion – situation 1*

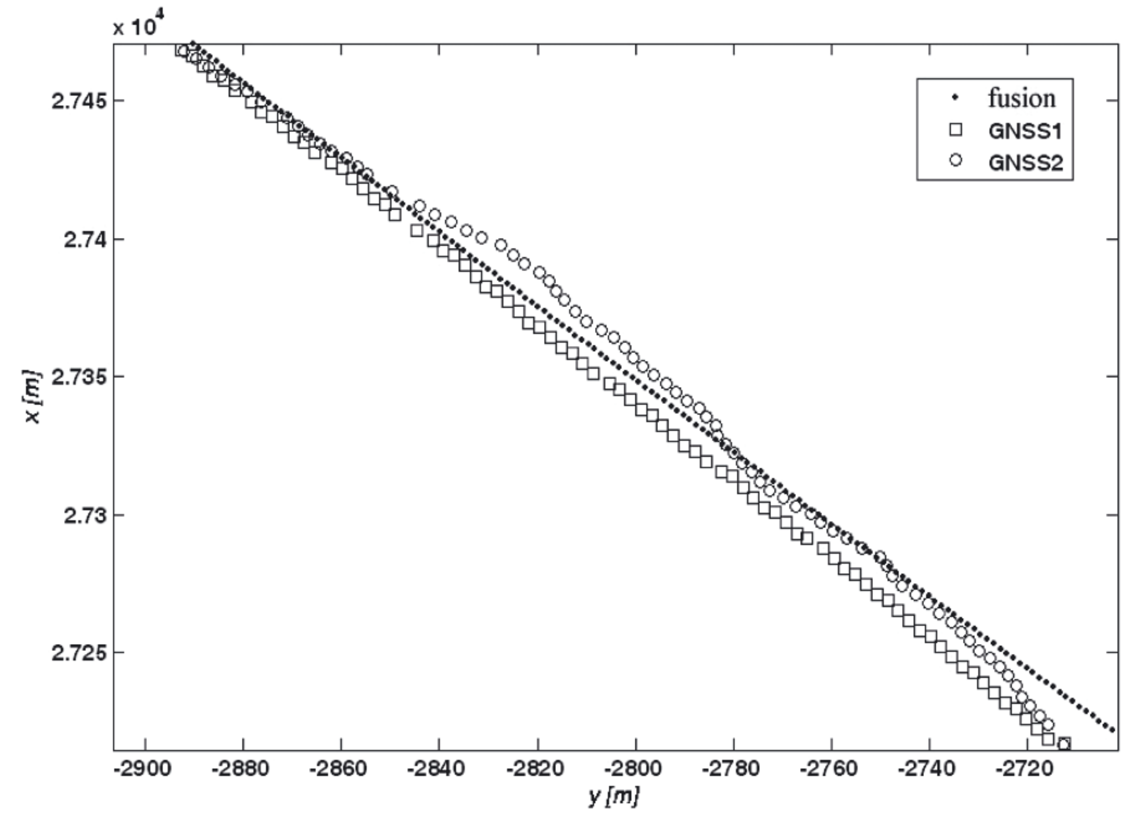

Fig. 5. *Ship's positions measured by $GNSS_1$ and $GNSS_2$ receivers and the measurement fusion – situation 2*

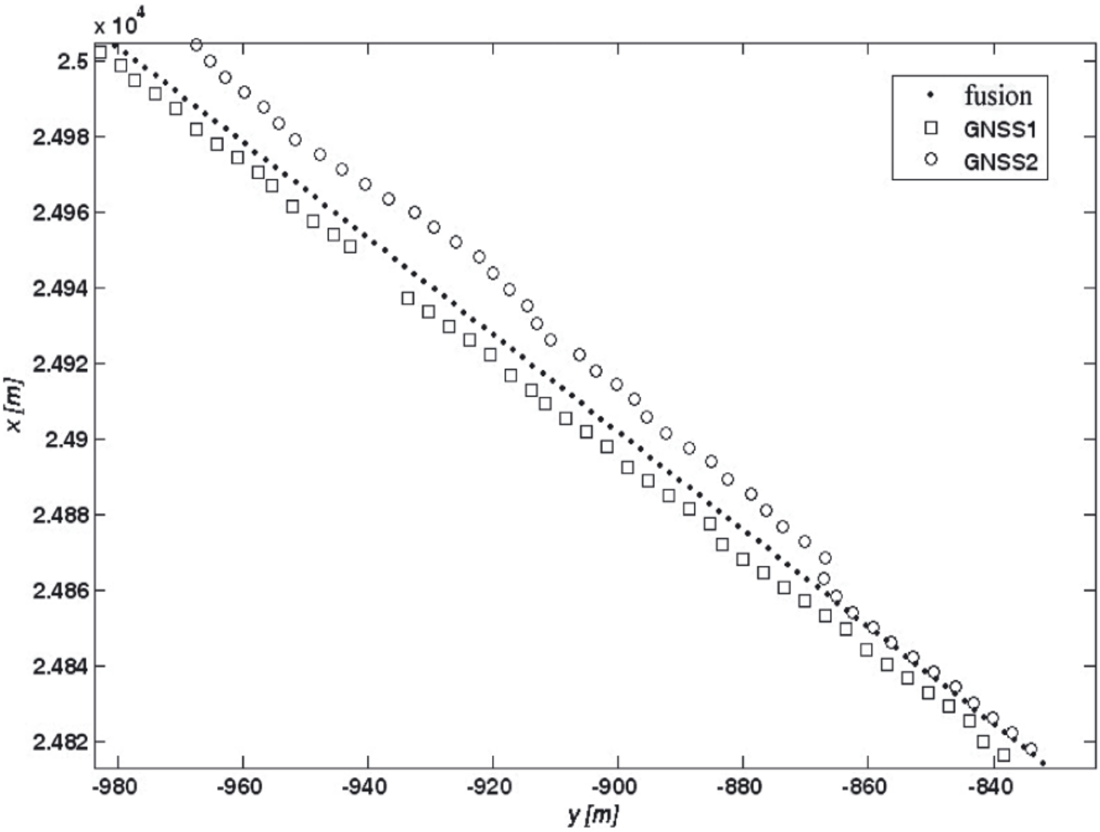

Fig. 6. Ship's positions measured by $GNSS_1$ and $GNSS_2$ receivers and the measurement fusion – situation 3

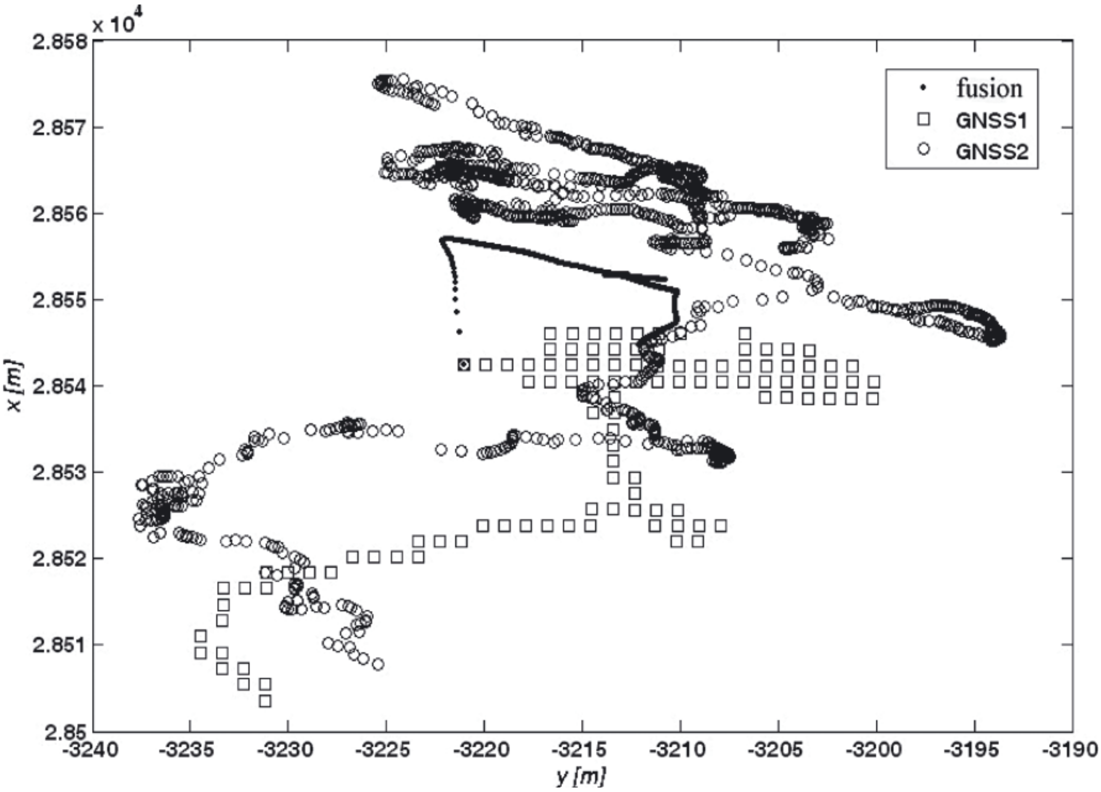

Fig. 7. Ship's positions measured by $GNSS_1$ and $GNSS_2$ receivers and the measurement fusion – situation 4

support system the measurement data fusion is the most proper, i.e. most stabilized.

The presented situations are typical for the overall test results. No case was observed when the fusion of measurement data from a rectilinear track section would be 'worse' that autonomous signals received from GNSS receivers.

SUMMARY

In this article the problem of navigational data fusion was analyzed. The discussed computing algorithm is based on a multi-sensor Kalman filter. The algorithm combines navigational data measurements received from single autonomous receivers.

Implemented in the navigational decision support system, it was verified on the m/s *Nawigator XXI*. The field tests have indicated that the used algorithm improves the accuracy and reliability of measurements of navigational parameters. This confirms the effectiveness of algorithm operation in real conditions.

It should be emphasized that the presented method can be also used in other systems, e.g. automatic control systems.

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