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SLAM AIDED INERTIAL NAVIGATION SYSTEM

ABSTRACT

The interdisciplinary nature of navigation leads us to drawing on knowledge contained in solutions used in related technical fields. An example of this trend is combining it with elements of robotics, in which SLAM (Simultaneous Localization And Mapping*)* is commonly used for positioning a vehicle. To calculate position changes, the location of characteristic objects on a continuously updated map of an environment is used. The attractiveness of the implementation of this technology in connection with marine navigational aids, stems from the possibility of enhancing positioning accuracy in harbor, off-shore or narrow areas. That is in the areas where there is a built up hydro-technical infrastructure, such as breakwaters, waterfronts or navigational infrastructure in the form of marked water fairways and anchorages. In this article an analysis of SLAM combined with INS (Inertial Navigation System) is carried out. It focuses on the possibilities of enhancing accuracy in fixing position coordinates for a submarine. The first part of the article presents a mathematical base for combining INS and SLAM using the Extended Kalman Filter. The second part describes a study on the accuracy in positioning a mobile robot (in this instance a wheeled vehicle) which employs a navigation system based on INS and INS aided SLAM. The final part of the article includes the results of the study and their analysis. It also contains generalized conclusions indicating advantages and disadvantages of the proposed solution.

Key words:
SLAM, inertial navigation, data fusion, Extended Kalman Filter.

INTRODUCTION

A claim can be made that robotics is one of the fastest developing fields of science. This is caused by greater and lower prices of the whole variety of technologies

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implemented in modern automation, image processing and robot navigation. With the passage of time SLAM has become more and more common in use. It can be a perfect tool for making position fixing with dead-reckoning navigation systems, which are characterized by the increase in error in the function of time, more accurate. INS used for navigation in submarines is an example of such a system. This system, after a longer period of operation, fixes positions with low accuracy, insufficient for safe navigation [4]. Therefore it is often integrated with a satellite navigation system. The latter is used for fixing, in long time intervals, a very accurate reference position (referred to in the course of dead-reckoning) which is against the principles of operational secrecy of such vessels. Combining INS and SLAM can prove very helpful in such a situation. A submarine should then dynamically build an environment map (seabed map) using passive sensors (cameras, hydrophones, magnometers) or active ones (sonar, echo-sounders, laser scanners). The sensors mentioned are, in most cases, part of the basic navigational equipment in a ship and for this reason the proposed solution can be easily implemented in the future. The continuously updated map of an environment and objects found on it (wrecks, point pollution, fishing nets) could be used for fixing positions employing SLAM.

This article makes an attempt to assess INS employing SLAM (with the Extended Kalman Filter) with regard to a possibility of improving accuracy in fixing position coordinates for a submarine. The assessment aims at showing the advantages and disadvantages of such a solution, and in this way allowing for a its better use in the maritime environment.

THE SLAM-BASED METHOD FOR POSITION FIXING

The point of departure for understanding the issue of fusing totally different methods for position fixing is to explain the principles of functioning of each of them. Position fixing by inertial navigation systems is based on indications on an orthogonally installed triad of gyroscopes and accelerometers. The calculation of a position fix is based on the known shift Δx, Δy, Δz, in relation to three axes in the coordinate system adopted for calculations:

$$\Delta x = \int_0^t Vx(t)dt; \tag{1}$$

$$\Delta y = \int_0^t Vy(t)dt; \tag{2}$$

$$\Delta z = \int_0^t Vz(t)dt; \tag{3}$$

$$V_x = \int_0^t a_x(t)dt; \tag{4}$$

$$V_y = \int_0^t a_y(t)dt; \tag{5}$$

$$V_z = \int_0^t a_y(t)dt, \tag{6}$$

where:

a_x, a_y, a_z — acceleration on particular axes;
V_x, V_y, V_z — velocity on particular axes;
dt — sampling time [3].

The accuracy of the position fix depends on the quality of the devices mentioned and decreases in the directly proportional relation to time. The components of the position fix error assume random direction. Therefore, depending on the moment of observation the error may increase or decrease. The INS system employed in submarines, which is characterized by the mean position error of 650 m as soon as after 30 minutes of work [2], can be referred to here as an example.

The departure point for developing the SLAM method were mobile robots using odometric data for their own positioning. The pioneers of the SLAM were Hugh Durrant-Whyte and John Leonard, who were the first to describe the idea of simultaneous mapping and localization at the beginning of the 1990s [1]. Seemingly simple activity for a human being to fix the change in own position relative to the change in location of other objects is not so primitive for a robot. It requires complex algorithms responsible for acquisition, detection and matching of the objects. It is only during the last two years and the development of the OPENCV library that it has become possible to make progress in this field [6].

In the case of a ship, position fixing in the SLAM method requires measurements (bearing and range) made with reference to characteristic objects observed in motion. Therefore, in order to fuse SLAM and INS an appropriate set of mathematical tools needs to be used. It must be capable of working out a compromise between two positions obtained from dead-reckoning (INS) and the results of measuring a bearing and a range (SLAM), taking into account theoretical magnitudes of errors made in fixing each position. In the investigations carried out the Extended Kalman Filter (EKF) was used as the set of mathematical tools.

It was assumed that a ship sails in the time interval τ. In each successive moment of navigation $k(k \in \tau)$ the shipboard INS fixes the increase in real course $\Delta KR_S(k)$ and increase in position coordinates $\Delta x_s(k), \Delta y_s(k)$, whereas other shipboard navigation devices fix real bearings $NR_{1\dots n}(k)$ and ranges $D_{1\dots n}(k)$ in relation to n characteristic objects.

It was also assumed that using the measurement results obtained in each successive moment $k+1$ the so called state vector $\mathbf{x}(k+1)$ is built. It is derived from the function $\mathbf{f}\big(\mathbf{x}(k), \mathbf{u}(k), \mathbf{w}(k)\big)$ describing the non-linear model of ship's movement [8]:

$$\mathbf{x}(k+1) = \mathbf{f}\big(\mathbf{x}(k), \mathbf{u}(k), \mathbf{w}(k)\big) = \begin{bmatrix} \mathrm{x_s}(k) \\ \mathrm{y_s}(k) \\ KR_S(k) \\ x_{l_1}(k) \\ y_{l_1}(k) \\ \vdots \\ x_{l_n}(k) \\ y_{l_n}(k) \end{bmatrix} + \begin{bmatrix} \Delta x_s(k) \cdot \\ \Delta y_s(k) \\ \Delta KR_S(k) \\ 0 \\ 0 \\ \vdots \\ 0 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} w_{x_s}(k) \\ w_{y_s}(k) \\ w_{KR_S}(k) \\ 0 \\ 0 \\ \vdots \\ 0 \\ 0 \\ 0 \end{bmatrix}, \tag{7}$$

where:

$x_s(k), y_s(k)$ — coordinates for ship's position fixed at moment k;

$x_{l_{1\dots n}}(k), y_{l_{1\dots n}}(k)$ — coordinates for navigational marks observed at moment k;

$w_{x_s}(k), w_{y_s}(k), w_{KR_s}(k)$ — so called random interference in fixing increase in coordinates and real course expressed in the form of errors having zero expected value at normal distribution.

In addition, at each moment $k+1$, using the function $\mathbf{h}\big(\mathbf{x}(k+1), \mathbf{v}(k+1)\big)$, determined is the so called observation vector:

$$\mathbf{z}(k+1) = \mathbf{h}\big(\mathbf{x}(k+1), \mathbf{v}(k+1)\big) = \begin{bmatrix} D_1(k+1) \\ NR_1(k+1) \\ D_2(k+1) \\ NR_2(k+1) \\ \vdots \\ D_n(k+1) \\ NR_n(k+1) \end{bmatrix} =$$

$$= \begin{bmatrix} \sqrt{\left(x_{l_1}(k+1) - x_s(k+1)\right)^2 + \left(y_{l_1}(k+1) - y_s(k+1)\right)^2} \\ \operatorname{atan} \frac{y_{l_1}(k+1) - y_s(k+1)}{x_{l_1}(k+1) - x_s(k+1)} \\ \sqrt{\left(x_{l_2}(k+1) - x_s(k+1)\right)^2 + \left(y_{l_2}(k+1) - y_s(k+1)\right)^2} \\ \operatorname{atan} \frac{y_{l_2}(k+1) - y_s(k+1)}{x_{l_2}(k+1) - x_s(k+1)} \\ \vdots \\ \sqrt{\left(x_{l_n}(k+1) - x_s(k+1)\right)^2 + \left(y_{l_n}(k+1) - y_s(k+1)\right)^2} \\ \operatorname{atan} \frac{y_{l_n}(k+1) - y_s(k+1)}{x_{l_n}(k+1) - x_s(k+1)} \end{bmatrix} + \begin{bmatrix} \nu_{D_1}(k+1) \\ \nu_{NR_1}(k+1) \\ \nu_{D_2}(k+1) \\ \nu_{NR_2}(k+1) \\ \vdots \\ \nu_{D_n}(k+1) \\ \nu_{NR_n}(k+1) \end{bmatrix}, \quad (8)$$

where:

$\nu_{NR_{1\ldots n}}(k+1), \nu_{D_{1\ldots n}}(k+1)$ — magnitude of error in bearing and range measurements in relation to the i-th navigational marking having the expected value equal to zero and normal distribution.

The functions $\mathbf{f}\left(\mathbf{x}(k), \mathbf{u}(k), \mathbf{w}(k)\right)$ i $\mathbf{h}\left(\mathbf{x}(k+1), \boldsymbol{\nu}(k+1)\right)$ are used for estimating ship coordinates in each successive moment $k+1$ following the Extended Kalman Filter algorithm presented in figure 1, where:

$\hat{\mathbf{x}}(k+1)$ i $\mathbf{P}(k+1)$ — estimated state vector and its covariance matrix, determined a posteriori at moment k + 1;

$\hat{\mathbf{x}}(k+1)^-$ i $\mathbf{P}(k+1)^-$ — estimated state vector and its covariance matrix, determined a posteriori at moment k + 1;

$\mathbf{F}(k+1) = \begin{bmatrix} \frac{\partial \mathbf{f}}{\partial(x_s, y_s, C_s)} & 0_{3x2n} \\ 0_{2nx3} & \mathbf{I}_{2nx2n} \end{bmatrix}$ — so called system matrix (where **I** is a unitary matrix);

$\mathbf{Q}(k)$ — interference matrix of state vector from moment k;

$\mathbf{P}(k)$ — updated covariance matrix of state vector used in successive a moment k + 1;

$\mathbf{W}(k+1) = \begin{bmatrix} \frac{\partial \mathbf{f}}{\partial\left(w_{x_s}, w_{y_s}, w_{C_s}\right)} & 0_{3x2n} \\ 0_{2nx3} & 0_{2nx2n} \end{bmatrix}$;

$\mathbf{H}(k+1) = \begin{bmatrix} \frac{\partial \mathbf{h}}{\partial(x_s, y_s)} & \frac{\partial \mathbf{h}}{\partial\left(x_{l_i}, y_{l_i}\right)} & 0_{2x2(n-1)} \end{bmatrix}$ — for i = 1 i n >1 (measurement to the first marking);

$\mathbf{H}(k+1) = \begin{bmatrix} \frac{\partial \mathbf{h}}{\partial(x_s, y_s)} & 0_{2x2(i-1)} & \frac{\partial \mathbf{h}}{\partial\left(x_{l_i}, y_{l_i}\right)} & 0_{2x2(n-i)} \end{bmatrix}$ — for 1< i < n (measurements to successive markings, except the last one);

$\mathbf{H}(k+1) = \left[\frac{\partial \mathbf{h}}{\partial(x_s, y_s)} \quad 0_{2x2(n-1)} \quad \frac{\partial \mathbf{h}}{\partial\left(x_{l_i}, y_{l_i}\right)}\right]$ — for $i = n$ (measurements to the first and last markings);

$$\mathbf{h}(\hat{\mathbf{x}}(k+1)^-) = \begin{bmatrix} \sqrt{\left(x_{l_i}(k+1) - \hat{x}_s(k+1)^-\right)^2 + \left(y_{l_i}(k+1) - \hat{y}_s(k+1)^-\right)^2} \\ \operatorname{atan} \frac{y_{l_i}(k+1) - \hat{y}_s(k+1)^-}{x_{l_i}(k+1) - \hat{x}_s(k+1)^-} \end{bmatrix};$$

$\mathbf{z}(k+1) = \begin{bmatrix} D_i(k+1) \\ NR_i(k+1) \end{bmatrix}$;

$\mathbf{R}(k+1)$ — interferencje matrix of state vector from moment $k + 1$;

$\mathbf{V}(k+1) = \left[\frac{\partial \mathbf{h}}{\partial(\nu_D, \nu_B)}\right]$.

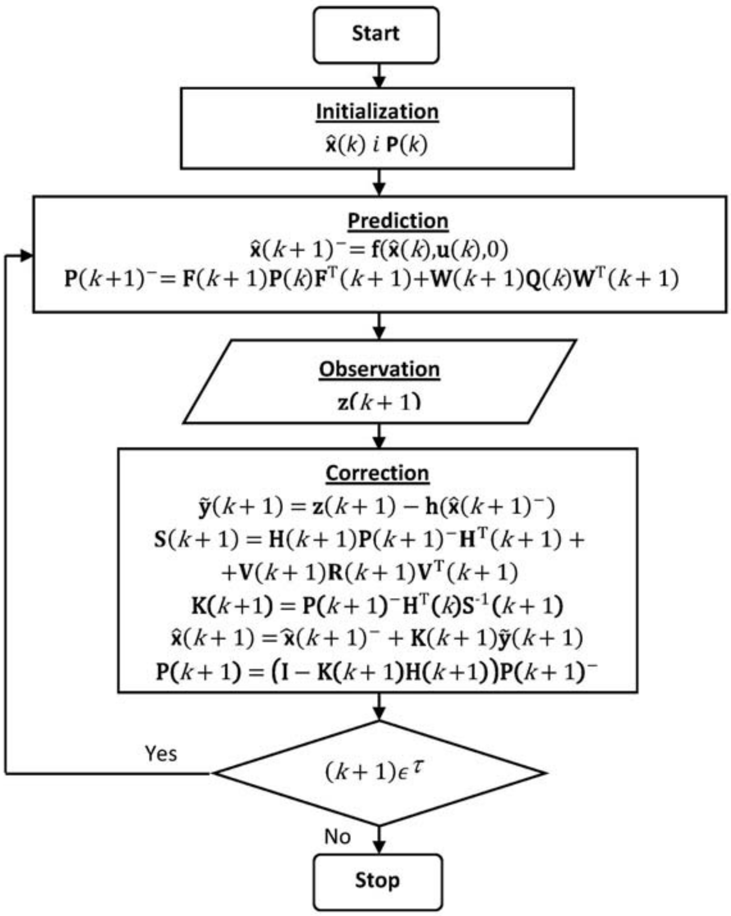

Fig. 1. The Extended Kalman Filter Algorithm [8]

THE ACCOUNT OF INVESTIGATIONS AND THEIR RESULTS

The investigations involved carrying out five tests with the investigation experiment method in similar to real life conditions. They were carried out using a mobile robot specially developed for the purpose of the tests (fig. 2). It is equipped with a navigational system composed of a microcontroller 'Arduino', INS module (type MPU 6050) and an ultrasonic range finder (type US 010) installed on a rotary servomechanism (type MG 966R) [5, 7, 15].

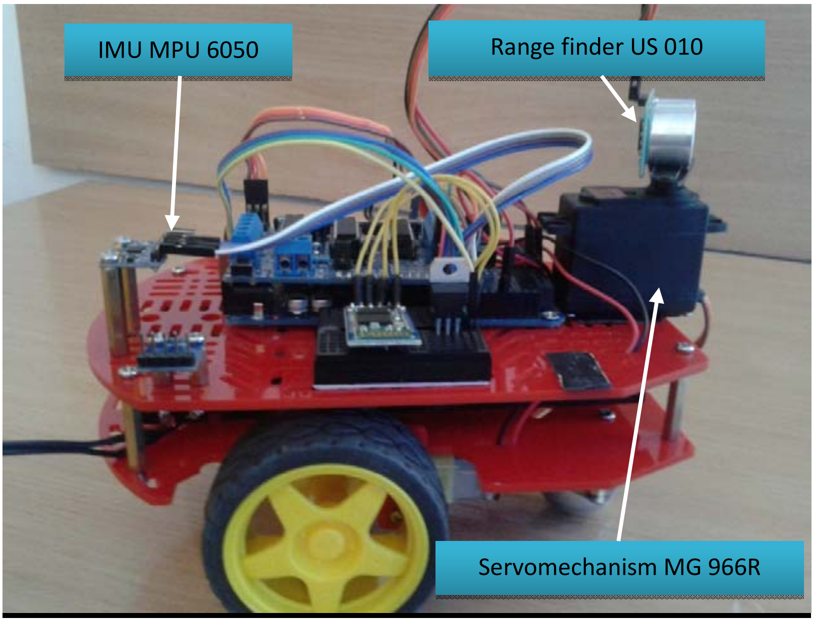

Fig. 2. A robot and elements of its navigation system

A singular test involved making measurements relating to a vehicle moving along a preset track running between two so called characteristic objects (location of the characteristic objects in relation to the track was somewhat different in each test. The position was fixed using only INS, and simultaneously INS combined with SLAM (fig. 3).

In the integrated variant (INS-SLAM), before the start of a test the vehicle (at the start position) was tasked with conducting observation of the environment and determining the location of the characteristic objects (fig. 4).

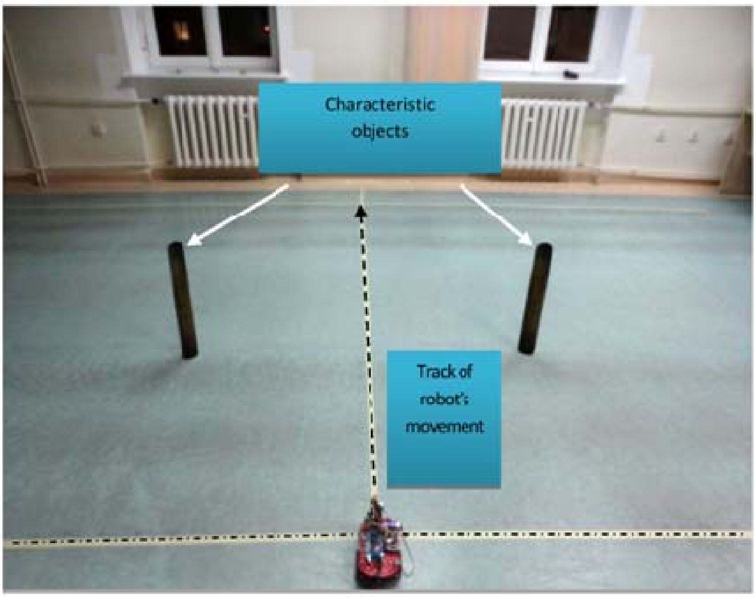

Fig. 3. Robot test track

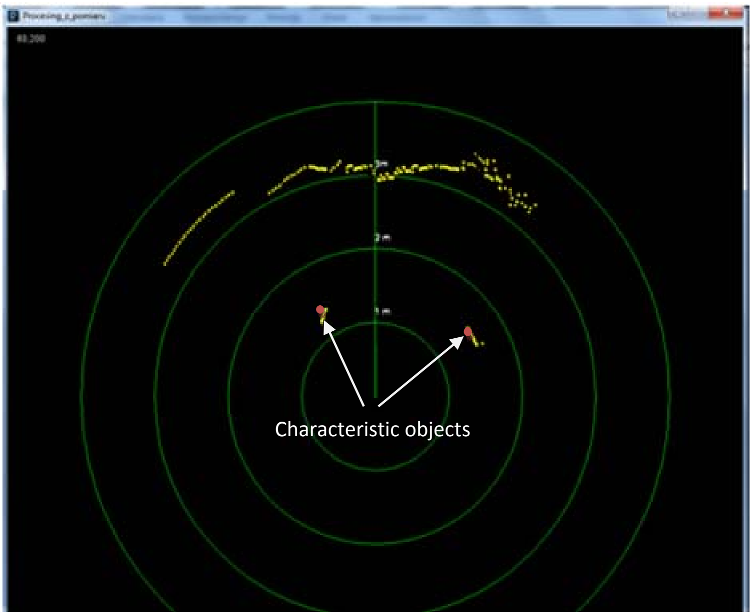

Fig. 4. View of a window of the 'Processing' software in the course determining location of characteristic objects [10]

Make a change in location along the track (to the moment k), during which it was calculating aggregate increase in real course $\Delta KR_S(k)$ and aggregate increase $\Delta x_S(k), \Delta y_S(k)$ in position coordinates based on momentary measurements by INS. Then again making an observation of the environment and determining real bearings $NR_{1\ldots n}(k)$ and range $D_{1\ldots n}(k)$ with regard to the characteristic objects (whose location was already known) after the change in its own position. Finally estimating coordinates $\hat{x}_S(k), \hat{y}_S(k)$ for the new position using EKF (see point 1).

In order to process measurements, calculated position coordinates and display of the image of the environment software developed for the microcontroller 'Arduino' and graphic environment 'Processing' was used [10].

The results obtained from the five tests are presented in a graphic form in figures 5–9.

Table 1 presents tabulated positions obtained from INS and INS-SLAM and their distance from real positions.

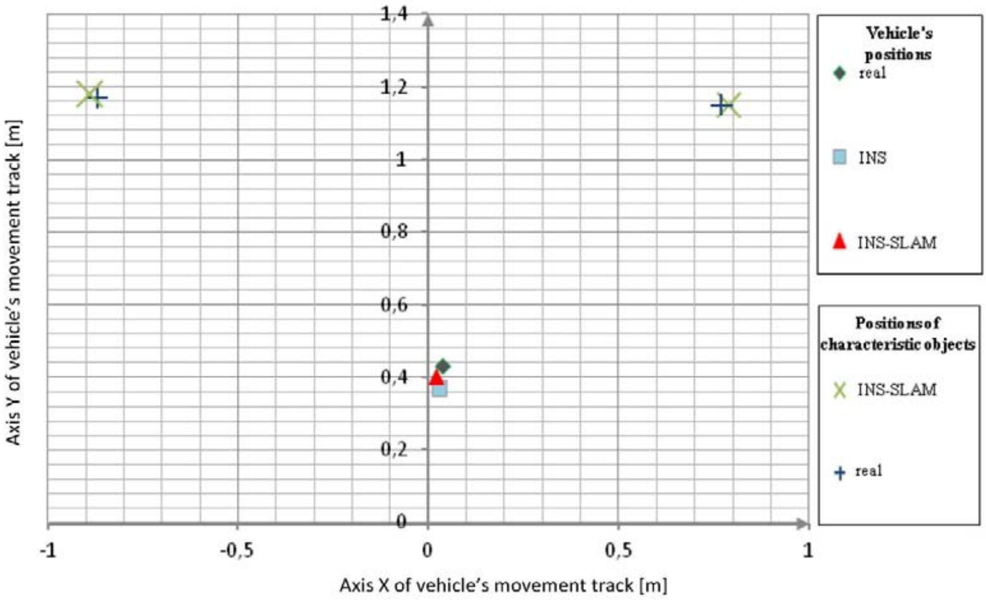

Fig. 5. Vehicle's positions obtained in the test No. 1

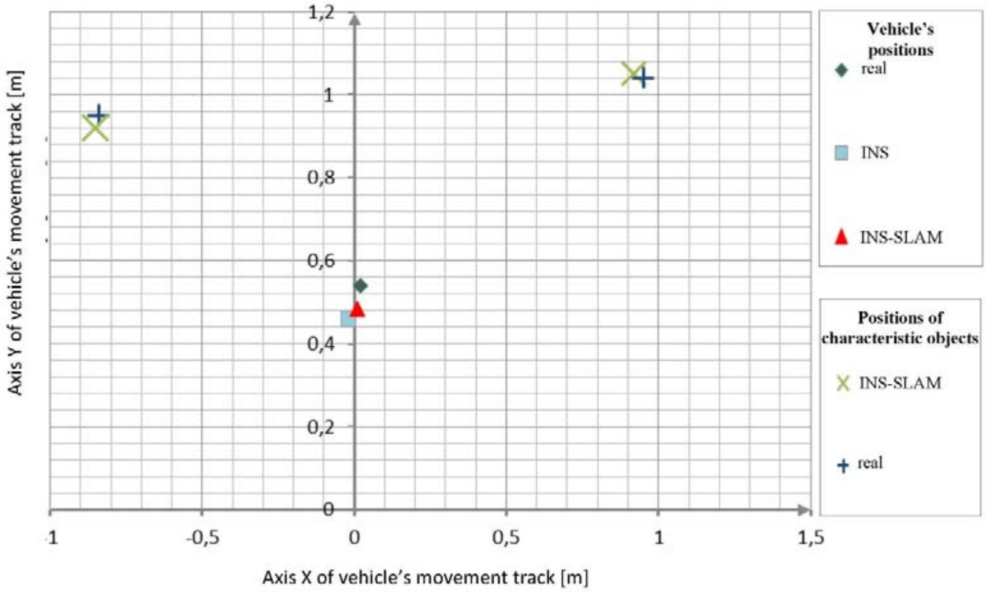

Fig. 6. Vehicle's positions obtained in the test No. 2

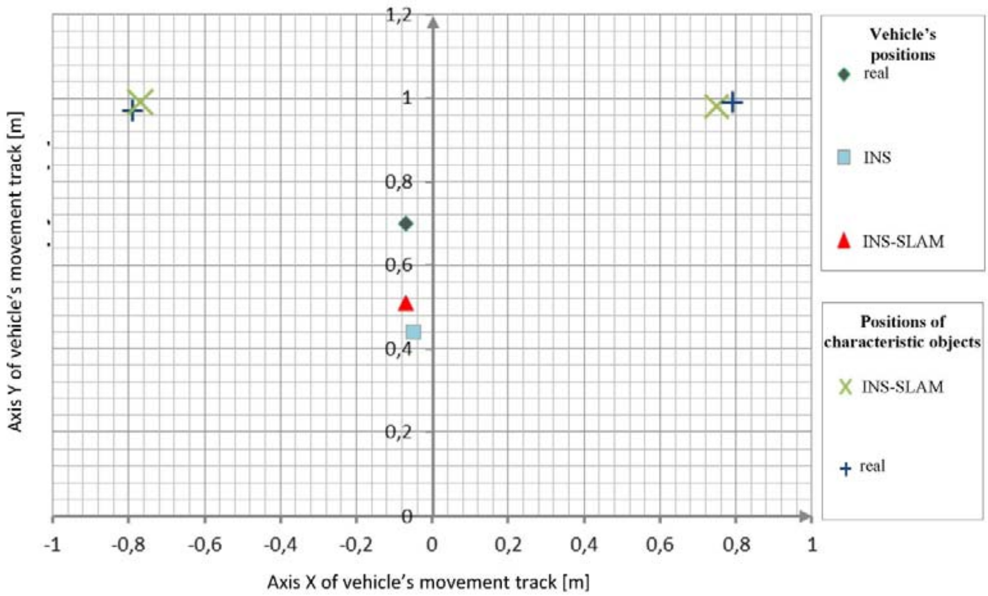

Fig. 7. Vehicle's positions obtained in the test No. 3

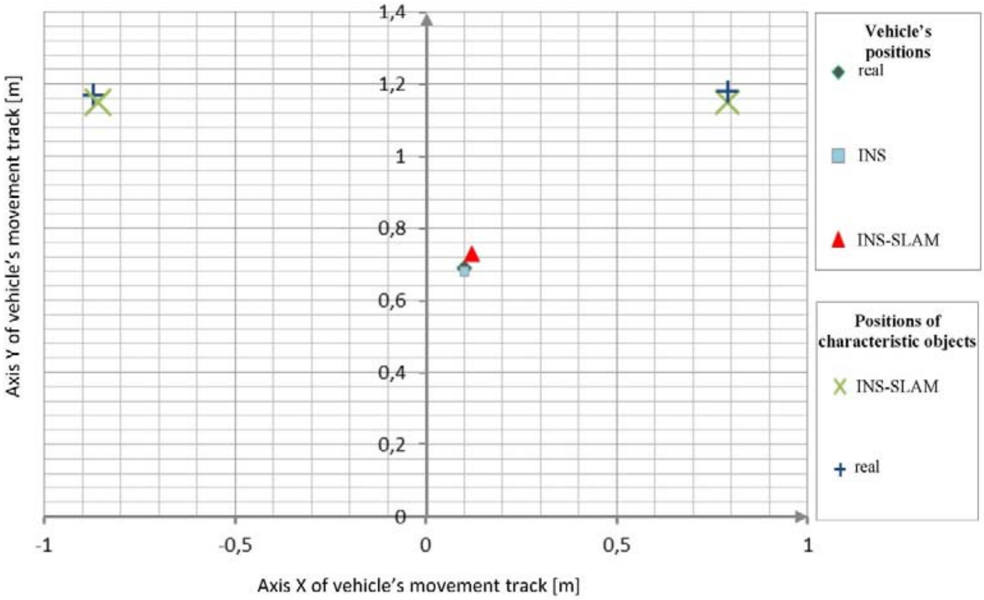

Fig. 8. Vehicle's positions obtained in the test No. 4

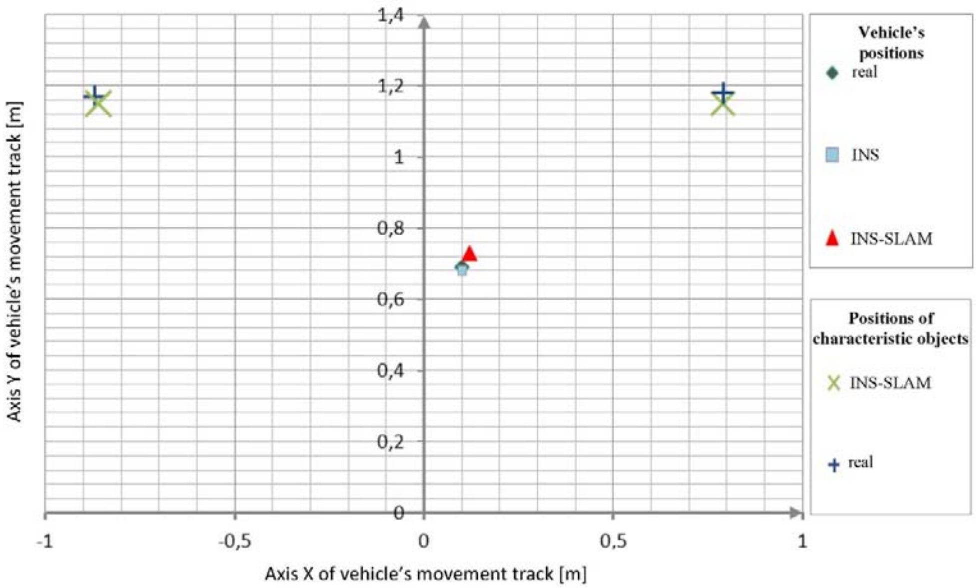

Fig. 9. Vehicle's positions obtained in the test No. 5

Table 1. Aggregate arrangement of the investigation results

Test No.	Real position [m]		Position from INS [m]		Position from INS-SLAM [m]		Distance between position from INS and position from INS-SLAM [m]	Distance between position from INS and real one [m]	Distance between position from INS-SLAM and real one [m]
	X	Y	X	Y	X	Y			
1	0,04	0,43	0,02	0,37	0,02	0,4	0,03	0,06	0,03
2	0,02	0,54	−0,02	0,46	0,01	0,48	0,04	0,09	0,06
3	−0,07	0,70	−0,05	0,44	−0,07	0,51	0,07	0,26	0,19
4	−0,02	0,58	−0,05	0,44	−0,04	0,56	0,12	0,14	0,03
5	0,1	0,69	0,1	0,68	0,11	0,73	0,05	0,01	0,04

CONCLUSIONS

It follows from figures 5–9 that in four out of five tests an increase in vehicle position accuracy was recorded. The error in a position was certainly caused by the fact that the range determined by the ultrasonic ranger to the characteristic objects differed to a small extent from the true range (the differences were up to 3% of the measured result), and the rotary servomechanism precisely set to the preset angular positions (with resolution up to 1%). It is exclusively the results of the test No. 4 that the position from INS is closer to the real position than the position from the INS-SLAM. It may stem from the fact that in this particular case the position from INS was worked out very accurately (its distance from the real one was as small as 1 cm). In the other cases, it may be claimed that the position correction by the SLAM system was carried out properly and the errors decreased.

It can also be said, based on the aggregate arrangement of results (tab. 1), that employing SLAM to correct a position from INS leads to a visible decrease in the position fixing mean error. During the tests, following the correction, a decreased position mean error by 00.6 m was recorded in relation to the mean INS position, which indicates usefulness of the presented method. The INS mean error following the SLAM correction was 00.9 m. The maximum distance of the real position from the INS-SLAM position was 0.19 m, whereas it was up to 0.26 m from the INS position. It can be expected that extending the time for testing and using better sensors to fix a bearing and range would have even more enhanced the difference in positioning accuracy using INS only and INS-SLAM (obviously in favor of INS-SLAM).

The obtained results have proved that the position correction method using SLAM is effective and in the future can be used for correcting positions of submarines.

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SYSTEM NAWIGACJI INERCJALNEJ WSPOMAGANY SLAM

STRESZCZENIE

Interdyscyplinarność nawigacji skłania do czerpania wiedzy z rozwiązań stosowanych w pokrewnych dziedzinach nauk technicznych. Przykładem jest połączenie z elementami robotyki, w której do pozycjonowania pojazdu powszechnie wykorzystywana jest technika SLAM (Simultaneous Localization And Mapping*)*. Polega ona na pozycjonowaniu pojazdu na podstawie zmian położenia obiektów charakterystycznych znajdujących się na stale aktualizowanej mapie otoczenia. Implementacja tej technologii w połączeniu z morskimi urządzeniami nawigacyjnymi zwiększa dokładność pozycjonowania w obszarach portowych, przybrzeżnych lub ścieśnionych, gdzie istnieje rozbudowana infrastruktura hydrotechniczna, np. falochrony, nabrzeża, oraz infrastruktura nawigacyjna w postaci oznakowanych torów wodnych i kotwicowisk. W artykule przeprowadzono analizę technologii SLAM w połączeniu z INS (Inertial Navigation System) pod kątem możliwości zwiększenia dokładności wypracowywania współrzędnych pozycji na okręcie podwodnym. W pierwszej części przedstawiono podstawę matematyczną zespolenia INS ze SLAM przy użyciu rozszerzonego filtru Kalmana (Extended Kalman Filter), w drugiej opisano badanie dokładności pozycjonowania robota mobilnego (pojazdu kołowego) wykorzystującego system nawigacyjny oparty na INS i INS wspomagany SLAM, na zakończenie przedstawiono wyniki badania oraz ich analizę, a także uogólnione wnioski ukazujące zalety i wady zaproponowanego rozwiązania.

Słowa kluczowe:
SLAM, nawigacja inercjalna, fuzja danych, rozszerzony filtr Kalmana.