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Navigation System Based on the Fuzzy Logic Expert System

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ABSTRACT

Existing approaches to closely integrating inertial navigation systems and a global navigation satellite system for mobile objects are based on the principle of redundancy. Kalman filtering is the most commonly applied mathematical tool, despite the fact that both the system itself and its measurement model are not ideal. By contrast, the use of situational control methods, which compare each class of situation to a clear, already known solution, enables us to abandon Kalman filtering and the problems associated with its implementation, in favor of an algorithm using an expert system to compile navigation information. This article describes the operation of a loosely-coupled navigation system based on satellite navigation and low-cost inertial MEMS sensors, with a fuzzy logic expert system acting as an aggregation algorithm.

Key words: loosely coupled navigation system, MEMS sensors, GNSS, fuzzy expert system, fuzzy logic.

1.INTRODUCTION

Existing approaches to closely integrating inertial navigation systems (INS) and a global navigation satellite system (GNSS) [15, 19] for mobile objects are based on the principle of redundancy. Kalman filtering [13] is the most commonly applied mathematical tool, despite the fact that both the system itself and its measurement model are not ideal [1, 2, 7].

By contrast, the use of situational control methods [3, 4, 8, 14, 16], which compare each class of situation to a clear, already known solution, enables us to abandon Kalman filtering and the problems associated with its implementation, in favor of an algorithm using an expert system to compile navigation information [9, 18].

2.METHOD DESCRIPTION

This article proposes an approach aiming to form and formalize expert knowledge on the situational significance of measurements from a substantiated set of mixed sensors which can be integrated into a mobile object's onboard navigation systems (figure 1).

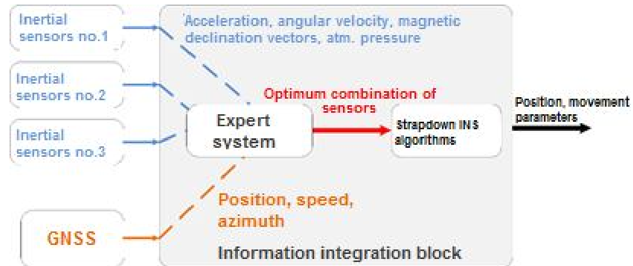

Figure 1: Algorithm based on an expert system

The essence of this navigation algorithm comprises two main tasks:

– identifying movement state;

– identifying movement type (turns, sharp maneuvers, etc.);

Further, on the basis of the identification values obtained, classic strapdown INS algorithms are applied, taking into account a substantiated choice of inertial sensors or the reinitialization process (recalibration including micromechanical sensors (MEMS)) (figure 2) [20-22].

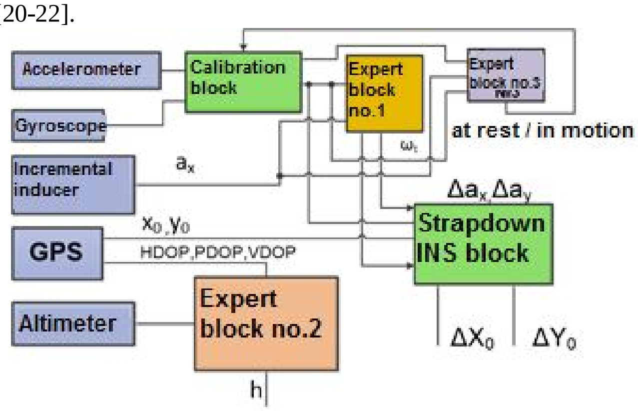

Figure 2: General algorithm for operation of a loosely coupled navigation system based on fuzzy logic

– the first expert block calculates the weight coefficients used to calculate the azimuth angle;

– the second expert block uses GNSS and altimeter data to calculate the object's height above sea level;

– the third expert block gives the object's dynamic state (at rest or in motion).

As shown by experiments evaluating the noise components of inertial micromechanical sensors (MEMS), data is optimally reliable during the first 2-5 minutes of operation, after which it becomes necessary to either reset the error, or implement a position assessment algorithm using extrapolation filters (figure 3)

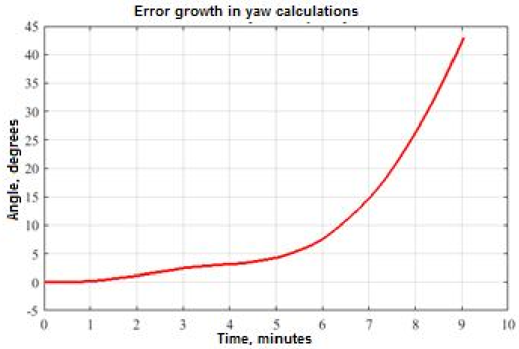

Figure 3: Error accumulation process during object position determination

The optimal moment to reset the error is when the object is completely immobile. Odometric information is often used to determine this condition, but it may not always be available, or may not take into account terrain movement peculiarities. Therefore, this article proposes using an expert system to identify the immobile condition, using sensor readings to determine the object's dynamic state.

At the same time, methods based on fuzzy logic, which allow processing of information from several sensors, are able to consider and detect the indistinct boundaries between dynamic states and at transitional points, for example, rotation, or uniformly accelerated linear movement under uncertain conditions. The object's position is assessed based on absolute values from inertial MEMS sensors, with the Mamdani [5, 6, 10-12, 17] model selected as transformation model, since it is the most flexible in describing transformation rules at a situational level with the help of linguistic variables. It follows that as soon as the intelligent component of the algorithm determines the type of movement, the most appropriate sensor can be used to improve position assessment and monitor error assessment.

3.KNOWLEDGE FORMALIZATION ALGORITHM TO IDENTIFY MOVEMENT TYPE

Before constructing the algorithm, it is necessary to determine the coordinate reference system and the method of transition from a connected coordinate system to a common one. The generally accepted coordinate system is NED, represented as follows: the x-axis is directed along the axis of motion, the y-axis is perpendicular to the axis of motion, and the z-axis is directed downwards (figure 4).

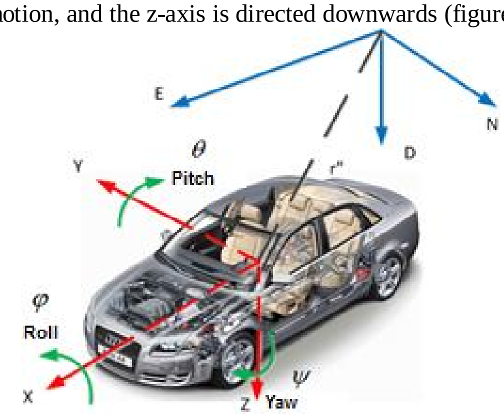

Figure 4: Object axes

Figure 4 also shows the Euler-Krylov angles, which determine the object's position in space

The object's axes are determined by the vector

$$\Lambda = \begin{bmatrix} \theta & \varphi & \psi \end{bmatrix}^T, \quad (1)$$

where $\theta -$ is the pitch angle; $\varphi -$ is the roll angle; $\psi -$ is the yaw angle.

The object's rotation vector is presented as

$$\Omega_\varepsilon = \begin{bmatrix} \dot{\theta} & \dot{\phi} & \dot{\psi} \end{bmatrix}^T = C_b^\varepsilon \Omega_b, \quad (2)$$

where

$$C_b^\varepsilon = \begin{bmatrix} 1 & \sin\phi \cdot tg\theta & \cos\phi \cdot tg\theta \\ 0 & \cos\phi & -\sin\phi \\ 0 & \dfrac{\sin\phi}{\cos\theta} & \dfrac{\cos\phi}{\cos\theta} \end{bmatrix},$$

$$\Omega_\varepsilon = \begin{bmatrix} \omega_x & \omega_y & \omega_z \end{bmatrix}^T,$$

ω_x, ω_y and ω_z are the object's angular velocities in its coordinate system.

In turn, the Euler-Krylov angles can be calculated from the rotation vector as follows:

$$\Lambda = \begin{bmatrix} \theta & \phi & \psi \end{bmatrix}^T = \int \Omega_\varepsilon dt. \quad (3)$$

The inclinometer required by the algorithm can be included as a three-axis accelerometer, with angle readings calculated by the formulas:

$$\varphi = \arctan\left(\frac{a_x}{\sqrt{a_y^2 + a_z^2}} \right), \quad (4)$$

$$\theta = \arctan\left(\frac{a_y}{\sqrt{a_x^2 + a_z^2}} \right), \quad (5)$$

where a_x,a_y and a_z are the accelerometer readings.

Based on knowledge about the peculiarities of inertial sensors' operational and noise characteristics, the proposed algorithm can assess position more accurately by intelligently selecting motion parameters from several sensors, based on the following rules:

Rule 1. If the vehicle is turning, position assessment is calculated from the gyroscope readings by $\Lambda = \Lambda_{gyro}$, where $\Lambda_{gyro} = \begin{bmatrix} \theta_{gyro} & \varphi_{gyro} & \psi_{gyro} \end{bmatrix}^T$

here, the index *gyro* indicates that the data from the angular rate sensor (ARS), with angles θ_{gyro}, φ_{gyro} and ψ_{gyro} are calculated by formulas (1) and (3).

Rule 2. If the vehicle is not turning and not under linear acceleration, the pitch and roll angles can be calculated using the accelerometer readings. If the conditions for this rule are continuously met for a few seconds, it is possible to use acceleration data to adjust the gyroscope drift and reset errors in the roll and pitch angle calculations.

The Mamdani model was selected as one of the fuzzy logic device transformation options, because the range of input values is well known – 4 inputs and 2 outputs.

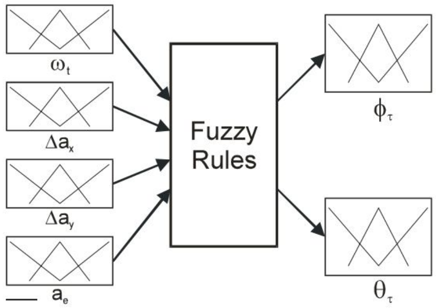

Figure 5: Expert system input and output values

The first input determines the rotation state, rotating the object along any of the axes, expressed by this formula:

$$\omega_t = |\omega_x| + |\omega_y| + |\omega_z|, \quad (6)$$

The second and third inputs determine acceleration from accelerometer readings, using the formulas

$$\Delta a_x = a_x[n] - a_x[n-1]$$
$$\Delta a_y = a_y[n] - a_y[n-1], \quad (7)$$

If $\Delta a_x \approx 0$ and $\Delta a_y \approx 0$, the object is standing still or moving at constant acceleration or moving along a road with a constant slope. The uncertainty of the "at rest/in motion" movement type can be solved by adding a fourth input based on the encoder readings or by using optical methods. The first derivative is the wheels' rotation speed:

$$a_\varepsilon = \Delta v_\varepsilon = v_\varepsilon[n] - v_\varepsilon[n-1], \quad (8)$$

where the index ε is data from the encoder.

The expert system's outputs are ϕ_τ and θ_τ the weight coefficients used to calculate pitch and roll angles based on accelerometer or ARS data. These coefficients range from 0 to 1 and are applied in the following formula:

$$\varphi = \varphi_{gyro} + (\varphi_a - \varphi_{gyro}) \cdot \varphi_\tau$$
$$\theta = \varphi_{gyro} + (\theta_a - \theta_{gyro}) \cdot \theta_\tau, \quad (9)$$

The form, location, and slope of the membership functions are determined by the following parameters:

− the form of terms was chosen considering the mobile object's movement dynamics during movement along unknown terrain, in which there are moderately sharp braking or acceleration stages;

− when compiling the membership functions, the entire range of input values was divided into three zones, described by the following linguistic variables: "slow", "medium" and "fast" for accelerometer readings, and "small", "medium" and "large" for ARS readings. Due to this, three terms were selected. It is also worth noting that it is possible to add terms, provided that the range of output values from inertial sensors is expanded;

− x-axis values correspond to the interval between accelerometer and ARS measurements while the object is in motion.

Rules of the form IF, THEN are presented below (part of the rules).

1. **If** change ω_t is not SLOW, **then** ϕ_τ and θ_τ are calculated from GYROSCOPE readings.
2. **If** changes Δa_x are HIGH, **then** ϕ_τ is calculated from GYROSCOPE readings.
3. **If** changes Δa_y are HIGH, **then** θ_τ is calculated from GYROSCOPE readings.
4. **If** changes ω_t are SLOW and Δa_y are MEDIUM **and** a_e are SMALL, **then** θ_τ is calculated from ACCELEROMETER and GYROSCOPE readings.
5. **If** changes ω_t are MEDIUM and Δa_x **and** a_e are SMALL, **then** ϕ_τ is calculated from ACCELEROMETER and GYROSCOPE readings.
6. **If** changes ω_t are MEDIUM and Δa_y **and** a_e are SMALL, **then** θ_τ is calculated from ACCELEROMETER and GYROSCOPE readings.
7. **If** changes ω_t are MEDIUM and Δa_x are not SMALL, **then** ϕ_τ is calculated from GYROSCOPE readings.
8. **If** changes ω_t are MEDIUM and Δa_y are not SMALL, **then** θ_τ is calculated from GYROSCOPE readings.
9. **If** changes ω_t are MEDIUM and a_e are not SMALL, **then** ϕ_τ and θ_τ are calculated from GYROSCOPE readings.

Membership functions are shown in figure 6.

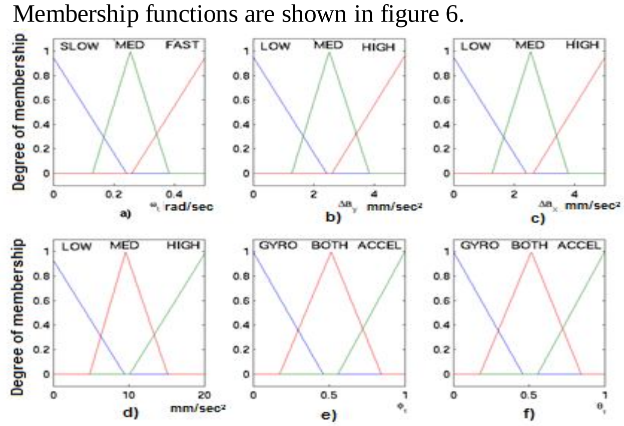

Figure 6: Membership functions: a, b, c, d inputs; e and f outputs

This approach towards obtaining the weight coefficients is subsequently used to calculate the roll and pitch angles using the MEMS readings. Since the roll and pitch angle readings affect the calculation of the yaw angle, reducing the error in this data leads to a more accurate yaw angle calculation.

4.DYNAMIC STATE IDENTIFICATION ALGORITHM

This algorithm determines a mobile object's movement status; its output is either "at rest" or "in motion". To correctly determine a mobile object's dynamics based on the MEMS readings, the algorithm must be able to identify the state of motion despite the uncertainties and inaccuracies associated with noise and interference in the measurements. The block diagram in figure 7 shows how the algorithm identifies a mobile object's dynamic state using fuzzy logic.

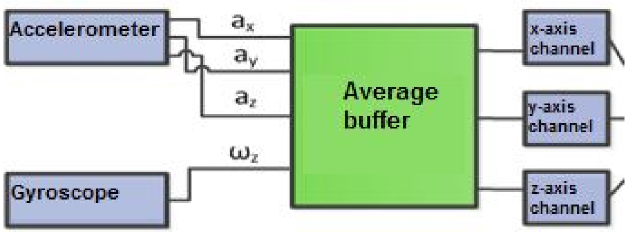

Figure 7: Block diagram for dynamic state identification algorithm

The algorithm can be divided into two components:

– saving the input values in the buffer of dimension *N* for the short period of time required for the subsequent equation, given as:

$$N \sim \{\nu_{MEMS}, \nu_{state}, t_p\} \quad (10)$$

where ν_{MEMS} – is the frequency of data output from MEMS sensors in Hz;

ν_{state} – is the rate of status release in Hz;

t_p – is the operation time of the identification unit in seconds.

The second important aspect determining the number of input channels, is the mobile object's vibration; in this case, using readings from three axes at once permits this indicator to be levelled when identifying the state of motion.

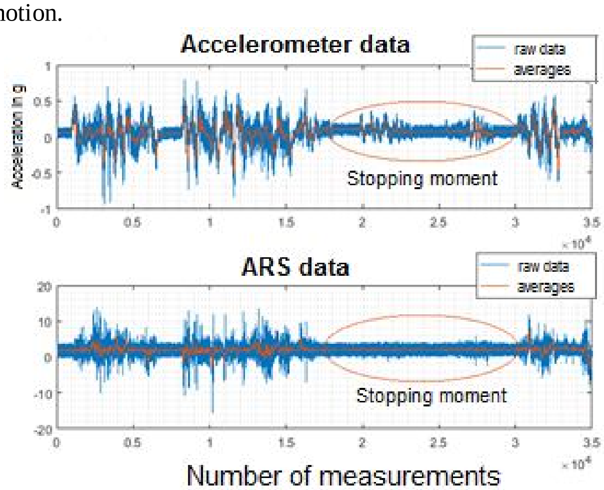

Figure 8: The object is at rest, but accelerometer data show an ambiguous state

The input parameters are the accelerometer x and y-axis values, and the average accelerometer readings and the z-axis DUS. In turn, the definition of input variables is described as follows:

$$AJ_x = \sum_{i=k-d}^{k} \left|(a_x)_i\right|$$

$$AJ_y = \sum_{i=k-d}^{k} \left|(a_y)_i\right|$$

$$AJ_z = \sum_{i=k-d}^{k} \left|(a_z + \omega_z)_i\right| \quad (11)$$

where, *k* is the current dimension;

d is the number of sample-values to be processed.

– an identification block based on an expert system with Mamdani transformation. Inputs are the readings from the sensor axes, and the output is a dynamic coefficient varying in the range from 0 to 1. A lower coefficient value indicates a high probability that the object is static. In turn, to compile a database of rules, the output data from an accelerometer and ARS installed on a car was analyzed. According to the results shown in figure 9, there are three ranges of valid accelerometer values:

1. the range of measurements during normal driving in an urban environment is shown in figure 9;

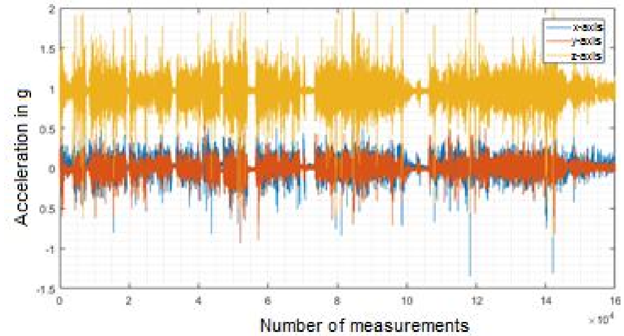

Figure 9: Test-run accelerometer data.

$$-0,5m/s^2 < a < 2m/s^2 \; ; (12)$$

2. the range of measurements when driving in dense urban traffic, figure 10.

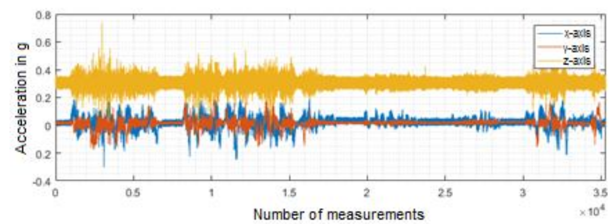

Figure 10: Accelerometer data during movement through traffic

$$-0,2m/s^2 < a < 0,4m/s^2 \; ; (13)$$

3. the range of measurements at which movement state can be "undefined", that is, very slow movement (rolling, or movement on an uneven surface).

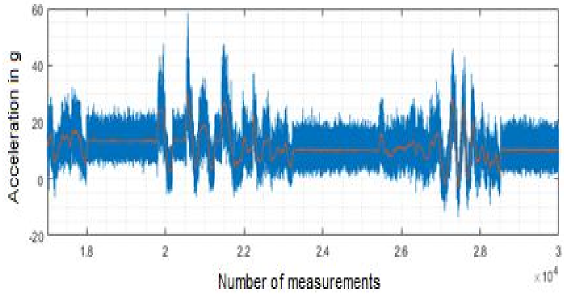

Figure 11: x-axis: accelerometer data while rolling

$$-0,1m/s^2 < a < 0,15m/s^2 \quad (14)$$

Based on equations (12) – (14), the ranges of values were chosen for the bases of triangular terms; the resulting final version of the configured membership functions and fuzzy rules is shown in figure 12 and table 1. Figure 13 shows the nonlinear transformation at the output of the expert block.

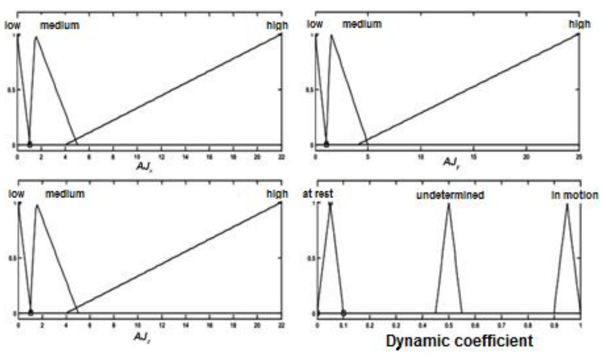

Figure 12: Expert system membership functions

Table 1: Fuzzy logic rules (part of the basic rules)

1	**If** change AJ_x is HIGH, **then** the object is IN MOTION.
2	**If** change AJ_y is HIGH, **then** the object is IN MOTION.
3	**If** change AJ_z is HIGH, **then** the object is IN MOTION.
4	**If** changes AJ_x, AJ_y, AJ_z are MEDIUM, **then** the object is IN MOTION.
9	**If** changes AJ_x AJ_z are LOW, and AJ_y,is MEDIUM, **then** status is UNDETERMINED.
10	**If** change AJ_x and AJ_Y are LOW, and AJ_z,is MEDIUM, **then** status is UNDETERMINED.
11	**If** changes AJ_x, AJ_y, AJ_z are LOW, **then** the object is AT REST.

The block's output is an assessment of the vehicle's dynamic status, which is determined by the linguistic variables: "at rest", "undetermined", and "in motion". As demonstrated by full-scale test experiments, the algorithm determines motion status with sufficient accuracy, but false positives can be observed during small linear displacements at the edge of the sensor's operating range. A small block of production rules has been added to eliminate this error (table 2). Rules 1 through 3 are key to the classification algorithm, they transform the coefficient into the status at rest/in motion. Rule 4 is necessary to detect instantaneous vehicle motion and avoid delayed detection using the average of accumulated data.

Table 2: Rules for identifying object movement status

Rule 1	***If*** *the dynamic coefficient is 0.95,* ***then*** *the object is MOVING.*
Rule 2	***If*** *the dynamic coefficient is 0.5,* ***then*** *the object is AT REST.*
Rule 3	***If*** *the dynamic coefficient is greater than 0.5, but less than 0.95, state of the object's state is determined by the previous state.*
Rule 4	***If*** *the current state is "at rest" and the value resulting from the sensors is greater than the specified criterion, the object is moving.*

Further, based on results from expert unit no.3, the effect of gyroscope drift on the yaw angle readings is reduced, algorithms for dynamic MEMS calibration can be included, and it is also possible to reset the errors accumulated in determination of the angles of the object's position in space, or make corrections using GNSS.

Figure 13: Mobile object trajectory through a dense urban area.

5.CONCLUSION

To conduct field experiments, a hardware and software complex with a loosely-coupled navigation system based on expert systems was developed and tested as part of autonomous mobile objects' control systems in dense urban areas. Test results showed an average increase in navigation accuracy of 20% compared to analogues. Figure 13 shows the algorithm's test trajectory.

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