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IMPLEMENTING THE SENSOR FUSION OF THE GYROSCOPE AND A COMPASS BASED ON THE KALMAN FILTER

This paper presents the accuracy enhancement of the observed magnetic declination by applying a sensor fusion algorithm. Sensor fusion is executed based on the Kalman filter, which uses the measurements of the gyroscope and the magnetometer (compass) and produces an estimate of the magnetic declination. The latter tends to be more accurate than the measurement itself. Implementation results of the Kalman filter are presented to verify the enhancement of the magnetic declination accuracy.

Keywords: sensor fusion, Kalman filter, compass, magnetometer, magnetic declination, gyroscope.

Introduction. Current MEMS motion sensors generate an output signal with some undesirable disturbances mixed. The presence of disturbances can cause unacceptable issues in the embedded systems. To reduce those irregular fluctuations from the observations, sensor fusion algorithms are used. Sensor fusion is a software, which combines data from several sensors to achieve more accurate and reliable system performance than it could be obtained by using only a single, individual sensor [1].

This paper produces a sensor fusion algorithm based on the observations of the gyroscope and the magnetometer (compass) to enhance the accuracy of magnetic declination. The implementation of the sensor fusion is done based on the Kalman filter. Kalman filter is an algorithm, which uses measurements from sensors acquired over time, and produces estimates of unknown variables that are considered more precise than those based only on a single measurement [2]. The main advantage of the Kalman model is that it is a recursive filter, and that it does not need to keep the measurements' history other than the state obtained at the previous time step [3]. Kalman filter is suitable for high-speed sensors, which makes it convenient for real-time problems [4].

The simulation of the real-time Kalman filter algorithm is executed in the system design platform LabVIEW, and the obtained results during the simulation procedure are presented in this paper.

Subject of investigation. The filtering operation of the Kalman model is based on LDS (Linear dynamical systems) discretized in a time domain. During each time step, a linear operator is applied to the previous state to compute the output state, with some disturbances mixed in, and optionally some information from the controls on the system if they are known [5].

CMPS2 anisotropic magneto-resistive digital compass is selected for magnetic declination measurement. With the three-axis Memsic's MMC34160PJ magnetometer on it, the sensor provides accuracy from 1 to 3 degrees. For the acquisition of yaw axis angular velocity, L3GD20H MEMS motion, a three-axis digital gyroscope is chosen. Both sensors are controlled by ATSAM3X8E 32-bit ARM core microcontroller. The microcontroller queries the observations from sensors and transmits them to the LabVIEW interface within a 10-millisecond time period. The Kalman filter is implemented in the LabVIEW environment for estimating the true state. The graphical software of the Kalman filter is presented in Figure 1.

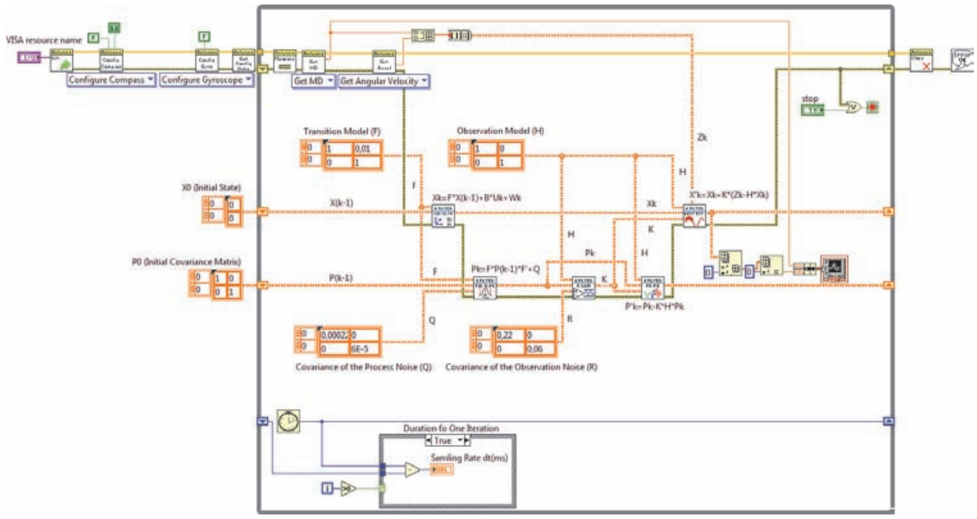


Fig.1. Implementation of the Kalman filter in the LabVIEW interface

The algorithm of the Kalman filter consists of two phases. The first phase called "Predict" phase, produces a prediction of the true state based on the previous state. The state of the Kalman filter is presented by two matrixes: the state estimate matrix $X_{k,}$ and the error covariance matrix P_k. The Kalman filter model supposes that the new state estimate at time k is obtained from the previous estimate (at k-1 time) by the equation below [6]:

$$X_k = F_k X_{k-1} + B_k u_k + w_k, \tag{1}$$

where

- $\mathbf{X}_k$ is the current state estimate (at time k);
- $\mathbf{X}_{k-1}$ is the previous state estimate (at time k-1);
- $\mathbf{F}_k$ is the state transition (prediction) matrix;
- $\mathbf{u}_k$ is the control vector;
- $\mathbf{B}_k$ is the control input matrix;
- $\mathbf{w}_k$ is the process noise, which is assumed to be drawn from zero mean multivariate normal distribution with covariance Q_k.

The state estimate matrix X_k contains two variables. The first variable is the magnetic declination value presented in degrees and the second variable is the angular velocity of yaw axis presented in degrees per second:

$$X_k = \begin{bmatrix} \alpha_{MD|k} \\ \omega_{z|k} \end{bmatrix}.$$

Based on the $\alpha_k = \alpha_{k-1} + \omega_k dt$ kinematic relation between the rotational angle and angular velocity (time period dt = 10 ms), the state transition matrix, which is applied to the previous state X_{k-1}, will be:

$$F = \begin{bmatrix} 1 & dt \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0{,}01 \\ 0 & 1 \end{bmatrix}.$$

Control-input matrix B_k and control vector u_k are set to zero matrixes by disregarding the control input variables. The virtual instrument (VI), which predicts the current state estimate according to equation (1), is presented in Figure 2. The F_k, X_{k-1}, B_k, u_k and w_k matrixes are declared as inputs and X_k is declared as an output matrix.

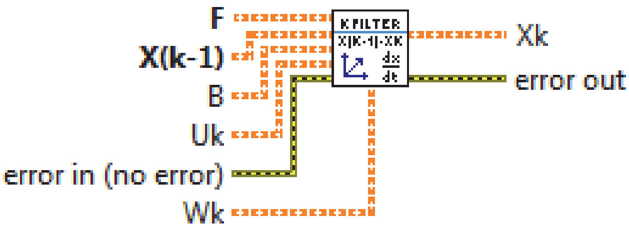


Fig.2. "Current state prediction" VI

The error covariance matrix at the current state (at time k) is obtained from the previous state (at k-1 time) according to [7]

$$P_k = F_k P_{k-1} F_k^T + Q_k, \quad (2)$$

where

- $\mathbf{P}_k$ is the error covariance matrix at the current state (at k time);
- $\mathbf{P}_{k-1}$ is the error covariance matrix at the previous state (at k-1 time);
- $\mathbf{F}_k^T$ is the transpose of F_k matrix, $F_k^T = \begin{bmatrix} 1 & 0 \\ 0{,}01 & 1 \end{bmatrix}$;
- $\mathbf{Q}_k$ is the covariance matrix of the process noise.

Covariance matrix Q_k is obtained during the testing procedure of the system:

$$Q_k = \begin{bmatrix} var(\alpha) & cov(\alpha, \omega_z) \\ cov(\omega_z, \alpha) & var(w_z) \end{bmatrix} = \begin{bmatrix} 0{,}00022 & 0 \\ 0 & 0{,}00006 \end{bmatrix}.$$

The virtual instrument, which predicts the covariance matrix based on equation (2), is presented in Figure 3. F_k P_{k-1}, Q_k matrixes are declared as input variables and P_k is declared as an output variable. The initial value of error covariance matrix P_0 is set to the identity matrix.

Fig.3. "Covariance matrix prediction" VI

After the accomplishment of the prediction phase, the current state is computed, and the Kalman filter obtains the observations from sensors. At time k, the observation matrix Z_k is made according to [8]:

$$Z_k = H_k X_k + v_k, \quad (3)$$

where

- $\mathbf{Z}_k$ is the observation at the current state (at time k);
- $\mathbf{H}_k$ is the observation model;
- $\mathbf{v}_k$ is the error observation noise which is assumed to be zero-mean The Gaussian white noise with covariance R_k.

The observation matrix Z_k consists of magnetic declination acquired by the compass and the angular velocity of the yaw axis measured by the gyroscope:

$$Z_k = \begin{bmatrix} \alpha_{MD|k|obs.} \\ \omega_{z|k|obs} \end{bmatrix}.$$

The H_k observation matrix is established as an identity matrix, due to the observation matrix Z_k and the current predicted state X_k are on the same scale:

$$H_k = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}.$$

During the second phase, which is called "Update" phase, the predicted state is fused with the current observation information to produce the best estimate of the state [9]. The information flow of the Kalman filter during the one time step is introduced in Figure 4.

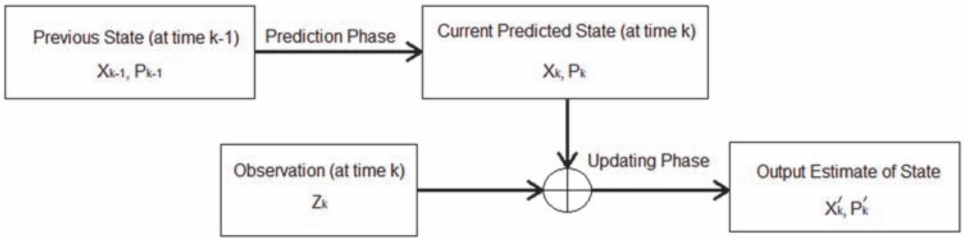


Fig.4. Kalman filter information flow

X_k' and P_k' are respectively the updated (best) state estimate and covariance matrixes. These matrixes are considered to be the output state of the Kalman filter. They are considered to be the output results of the current time step and, correspondingly, the initial variables for the next time step. They are computed by the equations below [10]:

$$X_k' = X_k + K'(Z_k - H_k X_k), \tag{4}$$

$$P_k' = P_k - K' H_k P_k, \tag{5}$$

where K' is the Kalman filter's gain which is calculated according to:

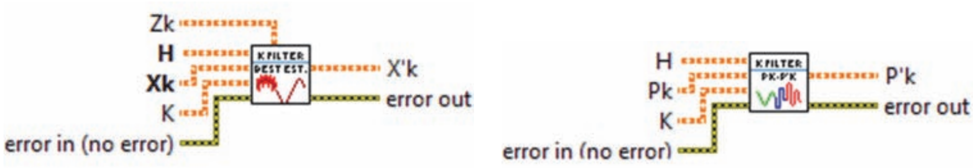
$$K' = P_k H_k^T \left(H_k P_k H_k^T + R_k \right)^{-1}. \tag{6}$$

R_k is the covariance matrix of the observation noise. Since the observations from the sensors are uncorrelated, the covariance of the measured MD and angular velocity will be zero. The variance of the measured magnetic declination and the variance of the measured angular velocity are obtained during the system testing procedure according to the sensor's accuracy:

$$R_k = \begin{bmatrix} var(\alpha_m) & cov(\alpha_m, \omega_{z|m}) \\ cov(\omega_{z|m}, \alpha_m) & var(\omega_{z|m}) \end{bmatrix} = \begin{bmatrix} 0{,}22 & 0 \\ 0 & 0{,}06 \end{bmatrix}.$$

The virtual instrument, which updates the state estimate based on the equation (4), is presented in Figure 5-a. The Z_k, H_k, X_k, and K matrixes are declared as inputs and X_k' is declared as an output.

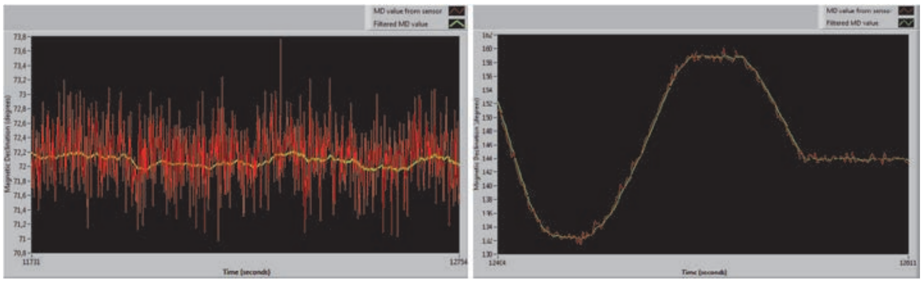
The updating process of the covariance matrix is done by “Updating covariance matrix” VI (Figure 5-b) based on equation (5). H_k, P_k, K are declared as input variables, P_k' is declared as an output variable.



a) b)

Fig.5. “Updating current state” VI (a), “Updating covariance matrix” VI (b)

Results of investigation. Figure 6 shows the obtained results when the system does not rotate (a), and the system rotates around the Z-axis (b). The red plot presents the magnetic declination (MD) acquired directly from the compass and the green plot presents the filtered magnetic declination value.



a) b)

Fig.6. The obtained results during the investigation. Red plot: MD value measured from the compass, green plot: the filtered MD value when the system does not rotate (a), and when the system rotates around the Z-axis (b)

Conclusion. The sensor fusion of gyroscope and magnetometer (compass) based on the Kalman filter is implemented in the LabVIEW environment. The investigation results are presented in Figure 6. The latter verifies that the Kalman filter enhances the accuracy of magnetic declination by more than 10 times.

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ԳԻՐՈՍԿՈՊԻ ԵՎ ԿՈՂՄՆԱՑՈՒՅՑԻ ՉԱՓՈՒՄՆԵՐԻ ՄԻԱՁՈՒԼՄԱՆ ԻՐԱԿԱՆԱՑՈՒՄԸ ԿԱԼՄԱՆԻ ՋՏԻՉԻ ՀԻՄԱՆ ՎՐԱ

Ներկայացված է չափված մագնիսական հակման արժեքի ճշտության լավարկումը՝ կիրառելով տվիչների միաձուլման ալգորիթմ: Տվիչների միաձուլումն իրականացված է Կալմանի զտիչի կիրառմամբ, որն օգտագործելով գիրոսկոպի և մագնիսաչափի (կողմնացույցի) չափումները՝ կատարում է մագնիսական հակման հաշվարկ: Վերջինս հակված է ավելի մեծ ճշգրտության, քան սկզբնական չափումը: Կալմանի զտիչի իրականացման արդյունքները ներկայացվում են՝ հաստատելու համար մագնիսական հակման ճշգրտության լավարկումը:

Առանցքային բառեր. տվիչների միաձուլում, Կալմանի զտիչ, կողմնացույց, մագնիսաչափ, մագնիսական հակում, գիրոսկոպ:

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СЛИЯНИЕ ИЗМЕРЕНИЙ ГИРОСКОПА И КОМПАСА НА ОСНОВЕ ФИЛЬТРА КАЛМАНА

Рассматриваются вопросы повышения точности измеренного магнитного отклонения путем применения алгоритма слияния датчиков. Слияние датчиков выполняется на основе фильтра Калмана, с помощью которого, используя измерения гироскопа и магнитометра (компаса), производится вычисление магнитного отклонения. Последнее имеет тенденцию быть более точным, чем само измерение. Представлены результаты реализации фильтра Калмана для подтверждения повышения точности магнитного отклонения.

Ключевые слова: слияние датчиков, фильтр Калмана, компас, магнитометр, магнитное отклонение, гироскоп.