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# Implement absolute orientation instruments for odometry system integrated with Gyroscope by using IKF

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**Abstract.** In this paper, absolute orientation instruments using compass are mainly proposed to estimate absolute orientation errors combined with estimated position and orientation from differential odometry integrated with gyroscope to calculate absolute orientation of mobile robot. In the method, the indirect Kalman filter is mainly used to estimate absolute orientation errors and the estimated errors are fed back to odometry system, and also estimates some parameter errors to correct encoder and gyroscope error. The simulation and experiment results show the estimated position and orientation of odometry system integrated with gyroscope, systematic errors of encoder and gyroscope and absolute orientation from compass compared with odometry system integrated with gyroscope.

**Keywords:** odometry system, absolute positioning, compass, indirect Kalman filter

## 1 Introduction

Typically, mobile robots behavior such as navigation, map building, the estimation of own position is very important. There are a lot of researches regarding the mobile robot in navigation such as [2, 4, 6, 7, 15, 20]. In navigation system can be categorized in relative and absolute positioning systems. The relative positioning system estimates a current position by using the information about previous positions and velocities. Basically, the method of estimation for a wheel type mobile robot's position uses the wheel encoder called odometry system. This is based on the wheel sensor readings of a differential-drive robot. In odometry (wheel sensors only) and dead reckoning (also heading sensors) the position update is based on sensors information. The movement of the robot sensed with wheel encoders or heading sensors or both, is integrated to compute position. Thus the position has to be updated from time to time by other localization mechanisms. Because the sensor measurement errors are integrated, the position error accumulates over time. However, these cumulative errors can be reduced by additional sensors. In outdoor environment, the estimated position by encoder has the unpredictable error caused by traveling over an unexpected small obstacle or a bump under the wheels. In this case, the accuracy of the estimated robot's position is suddenly getting worse. The position error is detailed in differential equation either inertia measurement unit (IMU) or support sensors nowadays with some solutions in textbook[5]. The analysis of navigation process from Kelly[11] is under special consideration about systematic error and theory on navigation. Also the compensation of position's error with redundant sensors is discussed[8, 13], however always limits on some redundant support systems. Despite these limitations, most researchers agree that encoder is an important part of a robot navigation system and that navigation tasks will be simplified if encoder accuracy can be improved. For example, the map-based positioning system is the method in absolute positioning system by using environment as landmark[9, 22]. A mobile robot builds a local map by using onboard sensors and compares the local map with a global map. If the features from local map and the global map match, an absolute position of the mobile robot is computed. Researches on

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the map-based positioning have been mainly focused on creating an accurate local map and estimating the positions by a map matching techniques. Cameras are the most complex sensors recently utilized due to high computational and memory requirements, as well as high cost in robotics. On researches in robotic field are using either local or global vision. In global vision, the camera is used as external instrument to monitor area, which covers both of the robot and environment. The global vision is easy to realize and widely used such as in factory environments or in robotic filed, i.e. the popular competition of robot soccer. The absolute positioning system estimates a current position measuring the position from predefined positions. The position errors of the absolute positioning system are bounded, because the information on previous positions is not required. However the absolute positioning system cannot provide absolute position information along path because of absolute positioning instrument's cost and operation in large area. Therefore, a hybrid navigation system plays an important role in combination of the relative or absolute positioning system by selection one from each category. Optimal localization should take into account the information provided by all of these sensors. A powerful technique for achieving this sensor fusion, called the Kalman filter[14]. It is a mathematical mechanism for producing an optimal estimate of the system state based on the knowledge of the system and the measuring device, the description of the system noise and measurement errors and the uncertainty in the dynamics models. Thus the Kalman filter fuses sensor information and system knowledge in an optimal solution. Optimality depends on the criteria chosen to evaluate the performance. Within the Kalman filter theory the system is assumed to be linear with Gaussian noise. This paper proposes two main points. The first point is the integration of absolute positioning instruments in navigation process, which can support mainly differential odometry system. For the second point the navigation parameter with complementary support system based on indirect Kalman filter (IKF) and with model of redundant error sources can compensate each other. The indirect Kalman filter can estimates the errors in the navigation and attitude information using the difference between inertial navigation system (INS) and external source data[16]. The error model is separated between systematic and non-systematic. The different measurement of error level is performed by complement of redundant support system. For all relevant navigation parameters is with concept of relative and absolute support system in form of external redundant source. In scope of hybrid approach the differential odometry and support system for our purpose are combined that the navigation problem in real-time can be solved. By the experimental test sensor information are from real physical sensors. In Section 2 describes the generally differential drive for mobile robot including encoder model. In Section 3 explains the widely relative support of gyroscope. The absolute orientation instrument, compass are explained in Section 4. The hybrid navigation system is described in Section 5. Simulations and experiments are presented in Section 6 and finally concludes the paper.

## 2 Mobile robot system

Generally, in navigation of mobile robot localization plays an important role. The robot's position is defined as $P_k = [X_k, Y_k, \theta_k]^\intercal$ and the next position $P_{k+1}$ is calculated from current position plus the position's increment both translation $\Delta S_k = [\Delta S_{x,k}, \Delta S_{y,k}]$ and rotation increment $\Delta\theta_k$ with reference to geometry as

$$P_{k+1} = P_k + \Delta S_k = [\Delta S_{x,k}, \Delta S_{y,k}, \Delta\theta_k]^\intercal. \tag{1}$$

With the increment $\Delta S_k$ and $\Delta\theta_k$ are used as couple function to construct mobile robot. In the differential drive system may consider that mobile robot move in curve path. Generally, the kinematics of differential drive consists of two wheels with wheel base $B_k$.

In Fig. 1 mobile robots are widely integrated with encoders at the left and right wheels, which generate the increment translation $\Delta S_{L,k}$ and $\Delta S_{R,k}$.

By the real robot path the parameter $B_k$, $\Delta S_{L,k}$ and $\Delta S_{R,k}$ behavior are not linear, because they are affected with error. These errors can not be solved by exact equation, however their state-space model can be considered as linear. With these errors can be separated in so called systematic and non systematic errors[3, 4, 12].

The wheel base is distance between both drive wheels as shown in Fig. 2. The distance B can not be exactly measured because it can change during running[4]. Uncertainty in the effective wheelbase is caused by

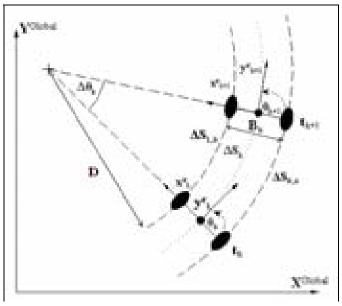

**Fig. 1.** Kinematics relation between $\Delta S_k, \Delta\theta_k, \Delta S_{L,k}$ and $\Delta S_{R,k}$

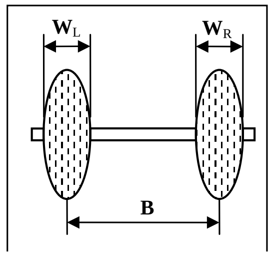


**Fig. 2.** Wheel base of a mobile robot

the fact that rubber tires, which do not contact the floor in one point, but rather in a contact area. This resulting uncertainty about the effective wheelbase can be changed always during the robot run. This generates wheel-base error $\Delta B_k$ and affects in Eq. (3) especially during fast turn. Therefore the rotation increment is affect by errors and the robot's orientation error is unbounded too.

In conclusion, the differential drive is an important system for mobile robot. To study the kinematic motion of mobile robot driven by differential drive, we defined parameters of robot motion in time interval $k$. The increment position of mobile robot can be calculated by above Eqs. (1) $\sim$ (3) and the cause of position error is mentioned too.

### 2.1 Model of differential drive system for navigation application

The basic concept of odometry is the transformation from wheel revolution to linear translation on the floor[1, 20]. This transformation is affected with errors by wheel slippage, unequal wheel diameter, inaccurate wheel base distance, unknown factor and others. The real increment translation of wheel encoder is prone to systematic and some non-systematic errors. The theoretical translation and rotation increment at the center of the robot is calculated by

$$\Delta S_k^t = \frac{\Delta S_{R,k}^t + \Delta S_{L,k}^t}{2}, \tag{2}$$

$$\Delta\theta_k = \frac{\Delta S_{R,k}^t - \Delta S_{L,k}^t}{B_k}. \tag{3}$$

Position extrapolation with theoretical encoder model is written as

$$P_{k+1}^t = P_k^t + \Delta P_k^t, \tag{4}$$

and is detailed below

$$X_{k+1}^t = X_k^t + \Delta S_k^t \cos\theta_k^t, \tag{5}$$

$$Y_{k+1}^t = Y_k^t + \Delta S_k^t \sin\theta_k^t, \tag{6}$$

$$\theta_{k+1}^t = \theta_k^t + \Delta\theta_k^t. \tag{7}$$

Incremental wheel encoders are based on the assumption that wheel revolutions can be translated into linear displacement relative to the floor. Wheel encoder error will occur, when if one wheel is to slip on, the associated encoder will not correctly correspond to a linear displacement of the wheel. In practice encoders are prone to various systematic and non-systematic errors in the detection of $\Delta S_{R,k}$ and $\Delta S_{L,k}$. The output of ideal wheel encoder is corrupted by systematic error from hardware imperfections as time and temperature varying scale factor errors[6]. From practical system inputs

$$\Delta S_{R,k}^p = (1 + \Omega_{R,k}) g \Delta S_{R,k}^t = \Delta S_{R,k}^t + \Omega_{R,k} g \Delta S_{R,k}^t, \tag{8}$$

$$\Delta S_{L,k}^p = (1 + \Omega_{L,k}) g \Delta S_{L,k}^t = \Delta S_{L,k}^t + \Omega_{L,k} g \Delta S_{L,k}^t. \tag{9}$$

and from Eq. (2), Eq. (3), Eq. (8) and Eq. (9) can be transformed in to a translation increment as

$$\Delta S_k^t = \frac{\Delta S_{R,k}^t + \Delta S_{L,k}^t}{2} = \frac{(\Delta S_{R,k}^t + \Omega_{R,k} g \Delta S_{R,k}^t) + (\Delta S_{L,k}^t + \Omega_{L,k} g \Delta S_{L,k}^t)}{2}. \tag{10}$$

and rotation increment

$$\Delta\theta_k = \frac{\Delta S_{R,k}^t - \Delta S_{L,k}^t}{B_k + \Delta B_k} = \frac{(\Delta S_{R,k}^t + \Omega_{R,k} g \Delta S_{R,k}^t) - (\Delta S_{L,k}^t + \Omega_{L,k} g \Delta S_{L,k}^t)}{B_k + \Delta B_k}. \tag{11}$$

Position with practical encoder model can be estimated as

$$X_{k+1}^p = X_k^p + \frac{(\Delta S_{R,k}^t + \Omega_{R,k} g \Delta S_{R,k}^t)\cos\theta_k^p}{2} + \frac{(\Delta S_{L,k}^t + \Omega_{L,k} g \Delta S_{L,k}^t)\cos\theta_k^p}{2}, \tag{12}$$

$$Y_{k+1}^p = Y_k^p + \frac{(\Delta S_{R,k}^t + \Omega_{R,k} g \Delta S_{R,k}^t)\sin\theta_k^p}{2} + \frac{(\Delta S_{L,k}^t + \Omega_{L,k} g \Delta S_{L,k}^t)\sin\theta_k^p}{2}, \tag{13}$$

$$\theta_{k+1}^p = \theta_k^p + \frac{\Delta S_{R,k}^t + \Omega_{R,k} g \Delta S_{R,k}^t}{B_k + \Delta B_k} - \frac{\Delta S_{L,k}^t + \Omega_{L,k} g \Delta S_{L,k}^t}{B_k + \Delta B_k}. \tag{14}$$

Firstly, the error state $\delta X$ can be calculated by subtraction of the theoretical position values from practical position values yields the error propagation equations

$$\delta X_{k+1} = \delta X_k + \frac{\Omega_{R,k} g \Delta S_{R,k}^t \cos\theta_k^t}{2} + \frac{\Omega_{L,k} g \Delta S_{L,k}^t \cos\theta_k^t}{2} - \frac{(\Delta S_{R,k}^t + \Delta S_{L,k}^t)\sin\theta_k^t g \delta\theta_k}{2}, \tag{15}$$

$$\delta Y_{k+1} = \delta Y_k + \frac{\Omega_{R,k} g \Delta S_{R,k}^t \sin\theta_k^t}{2} + \frac{\Omega_{L,k} g \Delta S_{L,k}^t \sin\theta_k^t}{2} - \frac{(\Delta S_{R,k}^t + \Delta S_{L,k}^t)\cos\theta_k^t g \delta\theta_k}{2}, \tag{16}$$

$$\delta\theta_{k+1} = \delta\theta_k + \frac{\Omega_{R,k} g \Delta S_{R,k}^t}{B_k} - \frac{\Omega_{L,k} g \Delta S_{L,k}^t}{B_k} + \frac{(\Delta S_{L,k}^t - \Delta S_{R,k}^t) g \Delta B}{B_k^2} \tag{17}$$

with the assumption that $\delta\theta_k$ is small then $\cos\delta\theta_k \approx 1, \sin\delta\theta_k \approx \delta\theta_k, \delta\theta_k g \Omega_{R,k} \approx 0, \delta\theta_k g \Omega_{R,k} \approx 0 and B_k \approx \Delta B_k$.Also the encoder scale factor of both wheels and wheel-base distance are regarded as random constants varying slightly in practice, so $\Omega_{R/L,k+1} = \Omega_{R/L,k}, \Delta B_{k+1} = \Delta B_k$. A first-order linearization of Eqs. (15) $\sim$ (17) can be evaluated by Jacobians method and the result of navigation system matrix is detailed as equation Eq. (18)

$$\begin{bmatrix} \delta X_{k+1} \\ \delta Y_{k+1} \\ \delta\theta_{k+1} \\ \Omega_{R,k+1}^o \\ \Omega_{L,k+1}^o \\ \Delta B_{k+1} \end{bmatrix} = \begin{bmatrix} 1 & 0 & -\frac{\Delta S_{R,k}^p + \Delta S_{L,k}^p}{2}\sin\theta_k^p & \frac{\Delta S_{R,k}^p \cos\theta_k^p}{2} & \frac{\Delta S_{L,k}^p \cos\theta_k^p}{2} & 0 \\ 0 & 1 & \frac{\Delta S_{R,k}^p + \Delta S_{L,k}^p}{2}\cos\theta_k^p & \frac{\Delta S_{R,k}^p \sin\theta_k^p}{2} & \frac{\Delta S_{L,k}^p \sin\theta_k^p}{2} & 0 \\ 0 & 0 & 1 & \frac{\Delta S_{R,k}^t}{B_k} & -\frac{\Delta S_{L,k}^t}{B_k} & -\frac{\Delta S_{R,k}^t + \Delta S_{L,k}^t}{B_k^2} \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \delta X_k \\ \delta Y_k \\ \delta\theta_k \\ \Omega_{R,k}^o \\ \Omega_{L,k}^o \\ \Delta B_k \end{bmatrix} \tag{18}$$

The state variable, using $X_k$ as the robot's position including some parameters of systematic errors is formulated as

$$X_k^o = [X_k, Y_k, \theta_k, \Omega_{R,k}^o, \Omega_{R,k}^o, \Delta B_k]^\intercal. \tag{19}$$

In conclusion the position and heading are computed by the differential encoder. All error sources are into one of two categories, which are systematic and non-systematic errors. Systematic errors are particularly considered, because they accumulate constantly, which can be reduced by careful mechanical design and by calibration. As the wheel diameter error (encoder scale factor error) and the wheel base error are the dominant systematic errors of the encoder, we are mainly concerned to reduce those errors using the gyroscope. Non-systematic errors are not directly caused by the kinematic properties of the vehicle, example, wheel-slippage or irregularities of the floor. With smooth floor, systematic errors cause much more to wheel encoders errors than non-systematic errors. On rough surfaces non-systematic errors are the dominant source of wheel encoder errors.

## 3 Mobile robot system integrated with gyroscope

The creation of relative support for differential odometry is the compensation both translation and rotation increment. The relative support can compensate error from odometry system for translation and rotation increment. With compensation by relative support system can reduce errors generated by noise. This paper presents also relative support system of rotation increment $\Delta\theta_k^G$ with gyroscope sensor. This work selects the commercial gyroscope CRS-03 (Silicon Sensing, 2000) working in measurement area $\pm 200^0/s$ and $\Delta\theta^G = 3.2^0 \pm 0.01^0$ shown in Fig. 3.

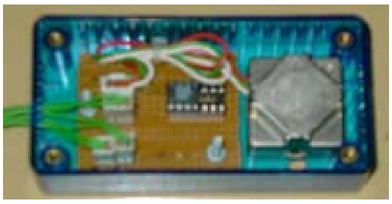

**Fig. 3.** Gyroscope CRS03 with temperature compensation

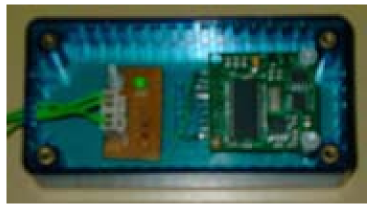

**Fig. 4.** The CMPS03 compass module

### 3.1 Gyroscope model

Many researchers on robotic field work on about gyroscope sensor[12, 21]. The theoretical gyroscope produces rotation increment in time interval $k$ defined as $\Delta\theta_k^{G,t}$. For position extrapolation with theoretical gyroscope is written as

$$\theta_{k+1}^{G,t} = \theta_k^{G,t} + \Delta\theta_k^{G,t}, \tag{20}$$
$$\Delta\theta_k^{G,P} = \Delta\theta_k^{G,t} + \Omega_k^G g \Delta\theta_k^{G,t}. \tag{21}$$

is corrupted by the scale factor error $\Omega_k^G$ and bias $\Psi_k^G$. For position extrapolation with practical gyroscope can be formulated as

$$\theta_{k+1}^{G,P} = \theta_k^{G,P} + \Delta\theta_k^{G,P} = \theta_k^{G,P} + \Delta\theta_k^{G,P} + \Omega_k^G g \Delta\theta_k^{G,P}. \tag{22}$$

The scale factor error $\Omega_k^G$ and bias error $\Psi_k^G$ can be regarded as random constants varying slightly in practical as $\Omega_{k+1}^G = \Omega_k^G$, $\Psi_{k+1}^G = \Psi_k^G$. The error state vector is calculated by subtraction of the theoretical orientation value from practical orientation value yields the error orientation propagation

$$\delta\theta_{k+1}^G = \delta\theta_k^G + \Omega_k^G g \Delta\theta_k^{G,t} + \Psi_k^G. \tag{23}$$

From a first-order linearization equation of gyroscope, the resulting time-variant perturbation model can be obtained by

$$\begin{bmatrix} \delta\theta_{k+1}^G \\ \Omega_{k+1}^G \\ \Psi_{k+1}^G \end{bmatrix} = \begin{bmatrix} 1 & \Delta\theta_k^{G,t} & 1 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \delta\theta_k^G \\ \Omega_k^G \\ \Psi_k^G \end{bmatrix} + W_G, \tag{24}$$

and

$$\delta\theta_{k+1}^G = A_k^G \delta\theta_k^G + w_k. \tag{25}$$

The state variable, using $x_k^G$ including parameters of systematic error is obtained as $x_k^G = [\theta_k^G, \Omega_k^G, \Psi_k^G]$. Combination of state-space localization model between odometry and gyroscope can be written as

$$\delta\theta_{k+1}^{OG} = A_k^{OG} \delta\theta_k^{OG} + w_k, \tag{26}$$

and detailed as Eq. (27).

$$\begin{bmatrix} \delta X_{k+1} \\ \delta Y_{k+1} \\ \delta \theta_{k+1} \\ \Omega^{o}_{R,k+1} \\ \Omega^{o}_{L,k+1} \\ \Delta B_{k+1} \\ \delta\theta^{G}_{k+1}\,\Omega^{G}_{k+1} \\ \Psi^{G}_{k+1} \end{bmatrix} = \begin{bmatrix} 1 & 0 & -\frac{\Delta S^{p}_{R,k}+\Delta S^{p}_{L,k}}{2}\sin\theta^{p}_{k} & \frac{\Delta S^{p}_{R,k}\cos\theta^{p}_{k}}{2} & \frac{\Delta S^{p}_{L,k}\cos\theta^{p}_{k}}{2} & 0 & 0 & 0 & 0 \\ 0 & 1 & \frac{\Delta S^{p}_{R,k}+\Delta S^{p}_{L,k}}{2}\cos\theta^{p}_{k} & \frac{\Delta S^{p}_{R,k}\sin\theta^{p}_{k}}{2} & \frac{\Delta S^{p}_{L,k}\sin\theta^{p}_{k}}{2} & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & \frac{\Delta S^{t}_{R,k}}{B_k} & -\frac{\Delta S^{t}_{L,k}}{B_k} & -\frac{\Delta S^{t}_{R,k}+\Delta S^{t}_{L,k}}{B^{2}_{k}} & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & \Delta\theta^{G,t}_{k} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \delta X_{k} \\ \delta Y_{k} \\ \delta\theta_{k} \\ \Omega^{o}_{R,k} \\ \Omega^{o}_{L,k} \\ \Delta B_{k} \\ \delta\theta^{G}_{k} \\ \Omega^{G}_{k} \\ \Psi^{G}_{k} \end{bmatrix} + W_k \tag{27}$$

The combination of odometry system and gyroscope is implemented by using different measurement model. The different measurement[12, 19] of rotation increment from the encoders and gyroscope is written as is calculated by

$$\delta Z^{OG}_{k} = \delta\Delta\theta^{O}_{k} - \delta\Delta\theta^{G}_{k} = \left\{\left[\frac{\Omega_{R,k} g \Delta S^{t}_{R,k}}{B_k} - \frac{\Omega_{L,k} g \Delta S^{t}_{L,k}}{B_k}, \frac{(\Delta S^{t}_{L,k} - \Delta S^{t}_{L,k}) g \Delta_k B}{B^{2}_{k}}\right] - [\Omega^{G}_{k} g \Delta\theta^{G,t}_{k}, \Psi^{G}_{k}]\right\} + v_k. \tag{28}$$

and detailed as Eq. (30)

$$Z^{OG}_{k} = \left[0, 0, 0, \frac{\Delta S^{t}_{R,k}}{B_k}, -\frac{\Delta S^{t}_{L,k}}{B_k}, \frac{\Delta S^{t}_{L,k} - \Delta S^{t}_{L,k}}{B^{2}_{k}}, 0, -\Delta\theta^{G,t}_{k}, -1\right] \left[\delta X_k, \delta Y_k, \delta\theta_k, \Omega^{o}_{R,k}, \Omega^{o}_{L,k}, \Delta B_k, \delta\theta^{G}_{k}, \Omega^{G}_{k}, \Psi^{G}_{k}\right]^{\mathsf{T}} + v_k. \tag{29}$$

General form of different model between odometry system and gyroscope can be written as

$$\delta\theta^{OG}_{k} = H^{OG}_{k} \delta X^{OG}_{k} + v_k, \tag{30}$$

where $v_k$ is the measurement noise.

In conclusion, gyroscope is proposed to combine with odometry system for error compensation. The indirect Kalman filter which feeds back the error estimates to the main navigation algorithm mutually compensates the differential encoder errors and the gyroscope errors. The dominant gyroscope random errors are the random bias and the scale factor error. Generally, the gyroscope output signal is not zero even though there is no input and the effect of the earth rotation is neglected. The bias error of gyroscope is the signal output from the gyroscope when it is not any rotation. It is one of errors from gyroscope output reading. The bias error tends to vary with temperature and over time. The scale factor relates the output of the gyroscope to the corresponding gyroscope rotation angle about its input axis. By error of the scale factor in gyroscope it means the deviation between the actual scale factor and the nominal scale factor. The output beat frequency changes with the changing of the scale factor when the input rate is the same, which affects precision of gyro directly.

## 4 Absolute orientation support with electronic compass

Absolute positioning systems use the geometry relation between the position and environment map[7]. From the geometry measurement the Cartesian coordinates $(X, Y, \theta)$can be specified under certain assumption. If the position of the geometry reference is known, the position of mobile robot can be calculated usually with good accuracy. Some methods have been proposed for robot position reference. One of them has designed landmarks placed at specified positions with respect to the reference coordinate system. The current position and orientation of the robot can be obtained by geometry transformations between robot sensors and these landmarks. Kabuka and Arenas[10] researched on absolute positioning by using barcodes. Many papers on the evaluation of a low cost gyroscope for application estimation of mobile robot systems were presented. However still needs other absolute sensing information and accurate error model for inertial systems. In this paper two absolute positioning systems are proposed. Kim described the experiments on orientation recovery of mobile robot by using compass. Ojeda[17] discussed on the use of electronic compasses in mobile robots with different error sources and solutions to correct these errors. The compass can generate direct the output of absolute orientation ($\theta_k^C$) located at the mobile robot's center. From the odometry system integrated with gyroscope, the mobile robot's orientation is estimated as $\theta_k^{OG}$.By subtraction of this estimated absolute orientation from measured absolute orientation from compass, the orientation error is obtained as

$$\delta\theta_k^{OG,C} = \theta_k^{OG} - \theta_k^C. \tag{31}$$

In conclusion, electronic compass is used to reference the absolute orientation of mobile robot as shown in Fig. 6. In this paper the CMPS03 compass module shown in Fig. 4 is used, specifically designed for mobile robot as an aid to navigation with resolution $\pm 0.1^o$[18]. The absolute orientation error between compass and odometry system will be fed in to the main algorithm to compensate the differential encoder errors and the gyroscope errors.

## 5 Hybrid navigation system from absolute positioning system

For this paper presents systems of main differential odometry integrated with gyroscope in mobile robot. Gyroscope generates rotation increment used to compensate rotation increment from differential odometry. The absolute positioning system for orientation with CMPS03 compass module (resolution $\pm 0.1^o$) is used as orientation reference.

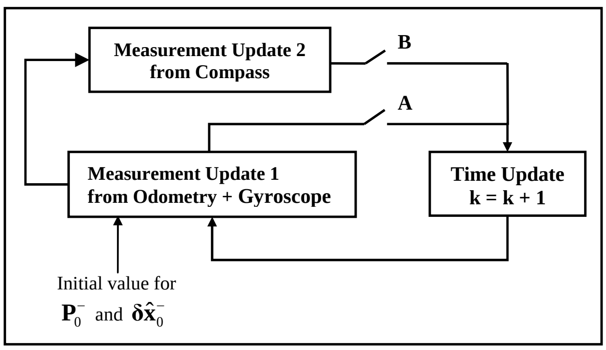


**Fig. 5.** IKF loop the combination of support system and odometry system in measurement step

The support systems are integrated in "Measurement Update" step of IKF algorithm in Fig. 5. If the connector $A$ is only closed by software, the IKF loop to combine main odometry system and gyroscope is started. The compass will be combined with the odometry system integrated with gyroscope in IKF loop, if connector $B$ is only close. The combination of compass with Odometry Integrated with Gyroscope, the state equation is obtained by Eq. (27). The measurement equation $Z_k = HX_k + v_k$ between odometry integrated with gyroscope system and compass can be given as

$$Z_k = \theta_k^{OG} - \theta_k^C = [\theta_k^{OG} - \theta_k^C] + v_k. \tag{32}$$

Then the measurement matrix of Eq. (33) is

$$Z_k^{OG,C} = [0,0,1,0,0,0,0,0,0][\delta X_k, \delta Y_k, \delta\theta_k, \Omega_{R,k}^o, \Omega_{L,k}^o, \Delta B_k, \delta\theta_k^G, \Omega_k^G, \Psi_k^G]^\intercal + v_k = H_k^{OG,C}\delta X_k^{OG} + v_k, \tag{33}$$

where $v_k$ is the measurement noise.

The main odometry integrated with gyroscope system and absolute positioning instruments[7, 22] is shown in Fig. 6.

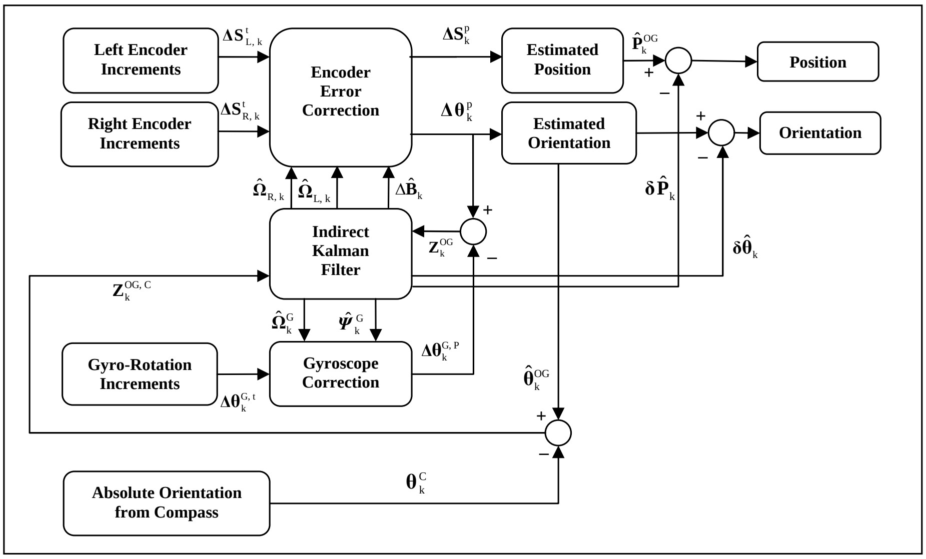


**Fig. 6.** Overall combinations of support system and odometry system

In conclusion, the combination of the support system with odometry system of mobile robot is different measurement in the same physical variable, i.e. rotation or translation increment or absolute orientation or position between odometry and external support system. Then the estimate of error state from IKF (Indirect Kalman Filter) is calculated to correct the navigation state. To estimate absolute orientation error, the different orientation between compass and odometry system integrated with gyroscope is used as a measurement value in IKF loop. In IKF loop error parameters of main system are also estimated and fed back to correct encoder error and gyroscope error.

## 6 Simulation and experimental results

The navigation error state from odometry $\delta X^o$ occurring during long trajectory and high dynamic environment is reduced by linear state vector and estimated by IKF algorithm. To keep the position estimation of mobile robot with pinpoint accuracy is based on the reciprocal error compensation between odometry error and gyroscope error.

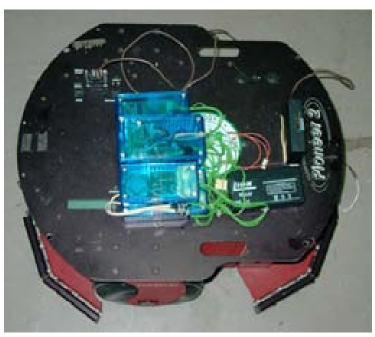

**Fig. 7.** Pioneer-II integrated with gyroscope and compass

The mobile robot (Pioneer-II from active media company) driven by differential odometry system integrated with gyroscope and compass shown in Fig. 7 is used for experiment in square shape 2.5×2.0 m. In Fig. 9 shows the orientation estimation. The red line represents the orientation of the robot from gyroscope system, the cyan line from mainly odometry system and the blue line is the combination of odometry and gyroscope by using different measurement of increment rotation with IKF algorithm. In Fig. 10 with IKF algorithm can be minimized the different orientation between odometry system and gyroscope at maximum $14^o$. Also systematic errors of odometry system are shown in Fig. 11 and gyroscope in Fig.12 and detail in Tab. 1.

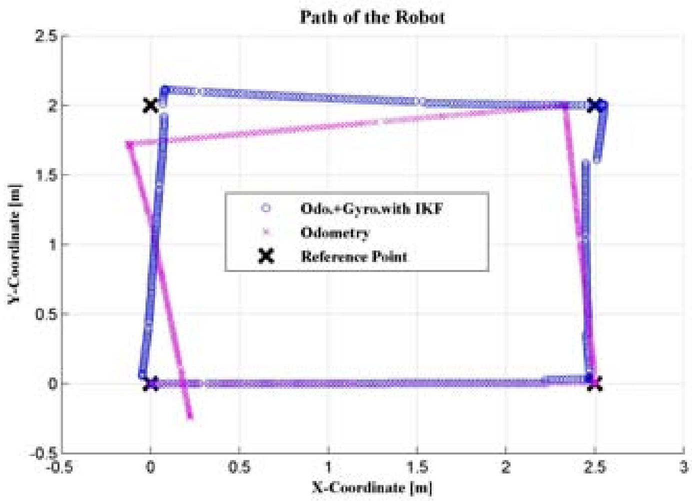


**Fig. 8.** Position generated by encoders is shown in cyan line and the blue line shows the position estimation of the robot by using different measurement of rotation increment between encoders and gyroscope with IKF algorithm

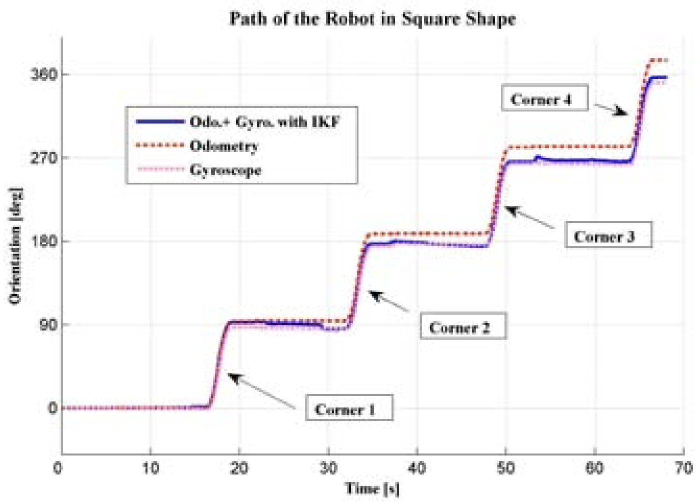


**Fig. 9.** Orientation of the robot in four corners with counter clockwise running

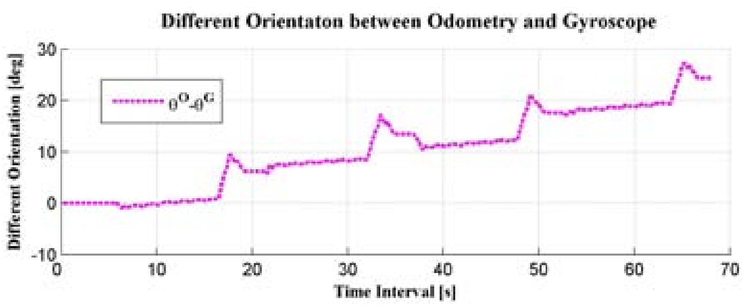


**Fig. 10.** Different orientation between odometry system and gyroscope

The cyan line represents the orientation from odometry, the red line from relative support of gyroscope, the blue line from absolute support of compass and the black line shows the combination of odometry system, gyroscope and compass by using IKF algorithm. The estimated orientation $\theta_k^{OG,IMF}$ is obtained from odometry with gyroscope support by using the first measurement update.

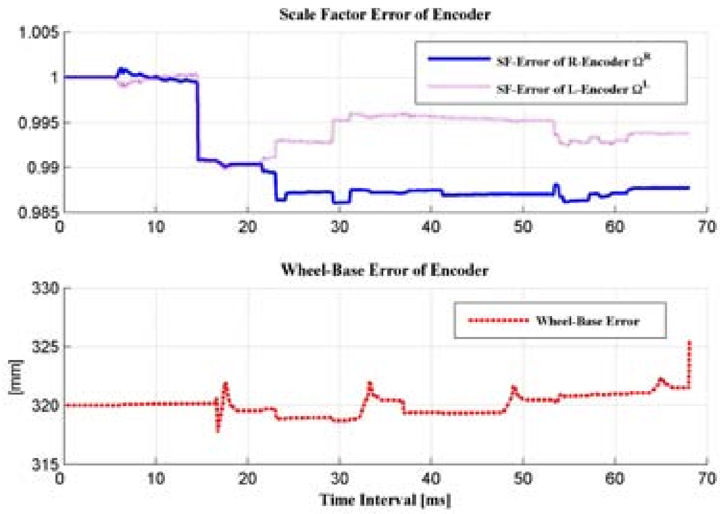


**Fig. 11.** Systematic error of odometry system

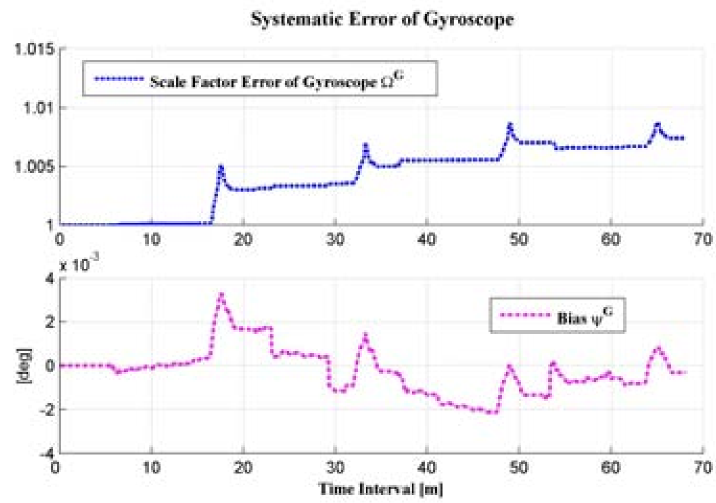


**Fig. 12.** Systematic error of gyroscope

**Table 1.** Systematic error of odometry system and gyroscope

| Systematic error of | Odometry | Gyroscope |
|---|---|---|
| Scale factor error of left encoder | $0.9962 - 1.0004$ | - |
| Scale factor error of right encoder | $0.9947 - 1.0010$ | - |
| Wheel-base error | $0 - 9$ mm | - |
| Scale factor error | - | $1.0000 - 1.0078$ |
| Bias error | - | $(-0.0004) - 0.0038$ |

In conclusion, for the navigation algorithm the reference position plays an important role. To reduce position error of odometry, the reference position must be known to find the difference position between odometry system and reference position in time. In experiment the robot starts at the position coordinate ($x = 0$, $y = 0$, $\theta = 0^o$) and runs from start point in right direction and returns at the start point again with speed 0.2 m/s. From experiment the robot's final position from odometry system are $P^{U^O}(X^{U^O} = 24.4\text{cm}$, $Y^{U^G} = -36.1\text{cm})$ and from odometry system integrated with gyroscope $P^{U^{OG}}(X^{U^{OG}} = 8.7\text{cm}$, $Y^{U^{OG}} = -12.4\text{cm})$ as shown in Fig. 8. The results of the orientation of mobile robot with gyroscope and compass support by using IKF algorithm are shown in Fig. 13. The different measurement of and shown in of $\theta_k^{OG,IMF}$ and $\theta_k^C$ shown in Fig. 14 will be passed to the third measurement update in Fig. 5 to reduce absolute orientation error.

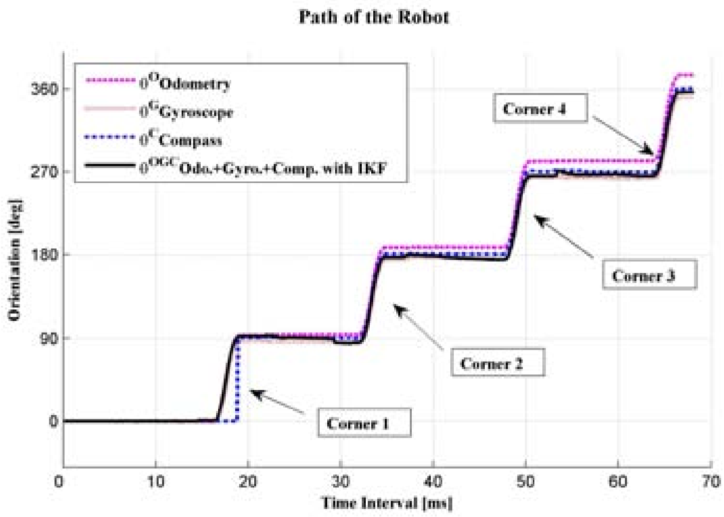


**Fig. 13.** Orientation of the robot from odometry, gyroscope, compass and the combination of main odometry system integrated with gyroscope and absolute positioning by using IKF algorithm

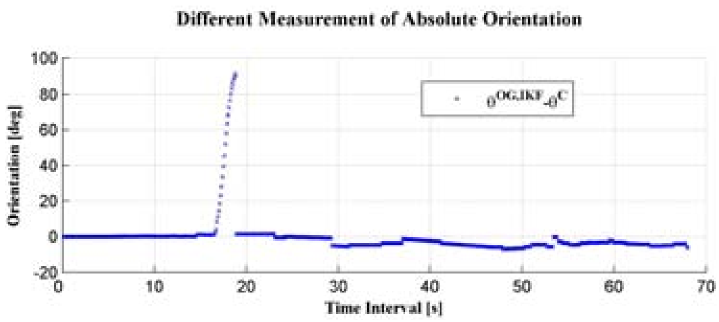


**Fig. 14.** Different absolute orientation between from main odometry integrated with gyroscope by using IKF algorithm and from compass

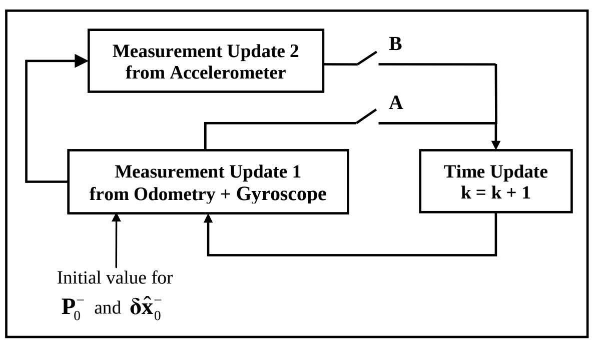


**Fig. 15.** Implementation of the translation increment for odometry system with an accelerometer

## 7 Conclusions

This paper proposed the hybrid absolute orientation system using compass for odometry system integrated with gyroscope for mobile robot in an indoor environment. To reduce the absolute orientation error compass is combined with odometry system integrated with gyroscope. The indirect feedback Kalman filter (IKF) is used as the combination of odometry system, gyroscope and the absolute orientation to estimate and compensate errors. The IKF can estimate the error of estimated absolute orientation by using the information from compass. Then mobile robot's position and orientation are obtained from addition the estimated position and orientation error with the estimated position and orientation from main system. Also the IKF estimated the scale factors of the encoders, the distance error between wheels and scale factor and bias errors of gyroscope to correct errors from encoders and gyroscope. The simulation results show that the IKF can give precisely estimated position and orientation by using absolute positioning system.

Future research aims to implement the translation increment for odometry system with an accelerometer. The support systems with accelerometer can be integrated in "Measurement Update" step of IKF algorithm in Fig. 15. If the connector $A$ is only closed by software, the IKF loop to combine main odometry system and gyroscope is started. The accelerometer will be combined with the odometry system integrated with gyroscope in IKF loop, if connector $B$ is only close. The complementary measurement between translation increment from encoder and accelerometer can be passed to the filter.

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