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RESEARCH ARTICLE

Study on the Fabrication of Prompt Power Measurement Device Using Low-Cost Inertial Sensor and Improvement of Accuracy

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Abstract

Currently, various measures of physical ability have been developed and used to improve the physical ability of athletes in the sports world. Circular activity is a very important and fundamental data for assessing the physical performance of most sports athletes, and studies are being conducted on various measures and methods to accurately measure this level of vigor. Several methods have been proposed and used using photodiodes, lasers, and high-speed cameras. In addition, devices for measuring instantaneous power using inertial sensors have been proposed and used. The inertial sensor has a very large error due to its measurement bias, and to overcome this, a Kalman filter is used. However, we design a Kalman filter that compensates for errors with only the IM without additional measurement, and we propose algorithms and measurement methods to achieve high accuracy even for low-cost IMs such as MPU9250, and then build a measurement device based on it. The results of the experiments show that the instantaneous force is measured accurately even for low--cost inertial sensors.

Keywords: Sprint speed; Prompt measurement; IMU; MPU9250; EKF

Introduction

Over the past few years, there has been a lot of research on navigation systems using inertial sensors. Especially, the low cost, small size and continuous improvement in performance of the inertial sensor have led to an increasing number of studies on various methods for measuring the nail power, the most basic indicator of the athlete's physical performance [1]. The GLSS methods, including GPS, are commonly used for instantaneous power measurements. These methods are convenient for portable devices and have relatively high measurement accuracy. However, it is highly influenced by indoor or meteorological conditions.The inertial sensor has a very large deviation of acceleration and angular velocity, which leads to a very large error in a short time in a navigation system that takes some time [5]. To solve this, the Extended Kalman Filter is generally widely used [4]. The error compensation methods according to the measured quantities include an acceleration or angular velocity moving average detection method [2], acceleration or angular velocity motion error detection method [3], and so on. Since nail power measurements are required to measure the movement of the player's waist, the player's azimuth is set up as a correct measurement and a filter is constructed.

Error Correction Method Based On Azimuth Detection

In general, when the position of the player is detected using an inertial sensor, the Kalman filter is used to compensate for the accumulated errors. Figure 1 shows the overall scheme.

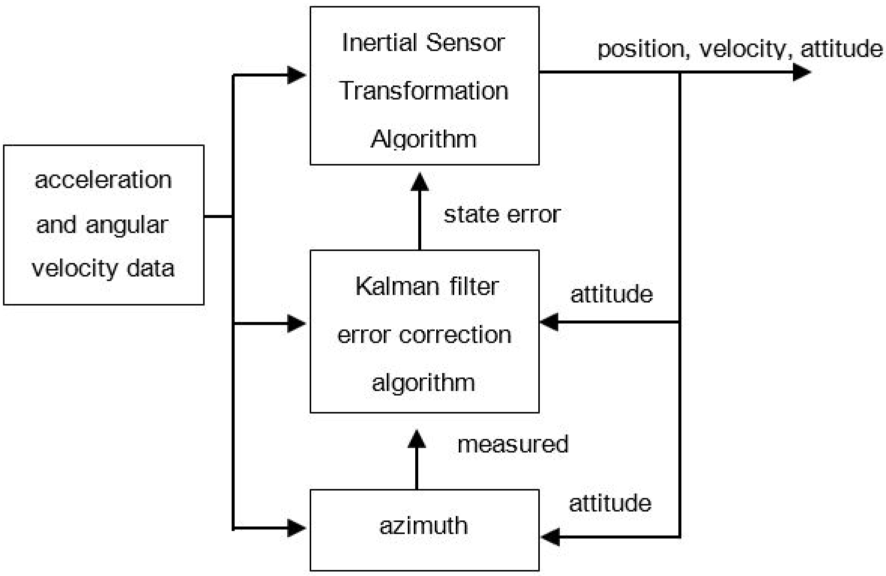

Figure 1: Flow chart of velocity measurement using azimuth angle

A Moving Object Velocity Measurement Algorithm

In the measurement using the IM, the initial attitude of the IM must be determined first. The acceleration values are used to calculate the shaft vibration angle and the shaft tilt angle, and the angular velocity values are used to determine the orientation. Initially, the direction of the athlete's departure is considered forward, so that the azimuth is set to zero. The roll angle and tilt angle are calculated as follows:

$$\text{roll} = \tan^{-1}\left(\frac{a_y^{\text{sensor}}}{a_z^{\text{sensor}}}\right) \quad (1)$$

$$\text{pitch} = -\sin^{-1}\left(\frac{a_x^{\text{sensor}}}{g}\right) \quad (2)$$

$$\text{yaw} = 0 \quad (3)$$

The a_x^sensor, a_y^sensor, and a_z^sensor mentioned here are the three-axis data of acceleration from the sensor and g is the acceleration of gravity.

The transformation matrix, which changes the acceleration and angular velocity of the sensor to the acceleration of the player, is defined as

$$C = \begin{pmatrix} \cos(pitch) & \sin(roll)\sin(pitch) & \cos(roll)\sin(pitch) \\ 0 & \cos(roll) & -\sin(roll) \\ -\sin(pitch) & \sin(roll)\cos(pitch) & \cos(roll)\cos(pitch) \end{pmatrix} \quad (4)$$

Using this transformation matrix, the acceleration of the player is calculated. The acceleration of the player is calculated by multiplying the transformation matrix by the acceleration of the sensor.

$$a_{x,y,z}^{\text{nav}} = C \times a_{x,y,z}^{\text{sensor}} \quad (5)$$

Here a_(x,y,z)^nav is the value of the player's three-axis acceleration.

In the measurement of the athlete's travel speed, the asymmetric matrix of the angular velocity matrix is calculated using the Kalman filter.

$$\Omega_k = \begin{pmatrix} 0 & -\omega_z & \omega_y \\ \omega_z & 0 & -\omega_x \\ -\omega_y & \omega_x & 0 \end{pmatrix} \quad (6)$$

The transformation matrices at each sampling point are computed from the transformation matrix at its previous point and the asymmetric matrix of angular velocity.

$$C_k = C_{k-1}(I_{3\times 3} + \Omega_k \Delta t)(I_{3\times 3} - \Omega_k \Delta t)^{-1} \quad (7)$$

Since the acceleration value used for the calculation is the sensor data, we perform a multiplication to the right. The player's acceleration is calculated from the sum of the transition matrix of the current state and its previous state.

$$a_k^{\text{nav}} = (C_k + C_{k-1}) \times a_k^{\text{sensor}}/2 \quad (8)$$

This is because the action takes place over time between the sample points. Hence, the velocity and position can be calculated by integrating respectively.

Extended kalman Filter

The extended Kalman filter is a regression algorithm to minimize the error covariance by iterating the prediction-update process continuously until the last sampling point [18].The filter uses a nonlinear model to predict the previous state of the system and to compensate for errors at the points of interest.However, there is a large accumulation of errors in the position and velocity calculated by the above method.Therefore, we apply the Kalman filter to compensate this as follows.Calculate the asymmetric matrix from the player's acceleration. This is a preliminary procedure for calculating the future Kalman gain.

$$S_k = \begin{pmatrix} 0 & -a_z^{nav} & a_y^{nav} \\ a_z^{nav} & 0 & -a_x^{nav} \\ -a_y^{nav} & a_x^{nav} & 0 \end{pmatrix} \quad (9)$$

We compute the state transition matrix that will transform the state quantity to the next state.

$$F_k = \begin{pmatrix} I_{3\times3} & 0_{3\times3} & 0_{3\times3} \\ 0_{3\times3} & I_{3\times3} & I_{3\times3}\Delta t \\ -S_k\Delta t & 0_{3\times3} & I_{3\times3} \end{pmatrix} \quad (10)$$

The state quantity at point K is calculated as

$$P_{k(-)} = F_k P_{k-1(+)} F_k^T + Q \quad (11)$$

$$P_{k(+)} = (I - K_k H) P_{k(-)} (I - K_k H)^T + K_k R K_k^T \quad (12)$$

Here Q is the covariance matrix of the Gaussian white noise of the system, P k is the state quantity at point k, where P_(k-1) represents the state quantity at point k-1.Here, + means the error-compensated state and – means the predicted quantity, i.e., the error-compensated state. R denotes the diagonal matrix of measurement noise. Next, we calculate the Kalman coefficient of the Kalman filter.

$$K_k = P_{k(-)} H (H P_{k(-)} H^T + R)^{-1} \quad (13)$$

This allows the correction of the state by calculating the error correction of the state.

$$P_{k(+)} = P_{k(-)} + K_k (Z_k - H_k P_{k(-)}) \quad (14)$$

Z k means the correct measurement at point k, and H k P_(k(-)) means the predicted measurement at point k.

Kalman Filter Design Using Azimuth Angle

We define the state quantity of the system as follows.

$$P_k = [\varphi_k,\ pos_k,\ vel_k] \quad (15)$$

Here, φ_k means the shaft vibration angle, shaft rotation angle, and yaw rotation angle, and the other two quantities mean position and velocity, respectively. In this paper, we observe the azimuth angle rather than any external support to know the exact measurement, so the exact measurement is expressed as

$$Z_k = yaw_k = 0, \quad H P_{k(-)} = \varphi_k^{(-)} \quad (16)$$

Thus, the state-quantity correction of the system is performed as follows.

$$P_{k(+)} = P_{k_{(-)}} - K_k \varphi_{k_{(-)}} \quad (17)$$

The compensated amount of the state of the system is K_k φ_(k(-)).

$$K_k \varphi_{k(-)} = [\Delta\omega_k,\ \Delta pos_k,\ \Delta vel_k] \quad (18)$$

Hence, error compensation is performed.

$$vel_{k(+)} = vel_{k(-)} - \Delta vel_k \quad (19)$$

$$pos_{k(+)} = pos_{k(-)} - \Delta pos_k \quad (20)$$

After correcting the system state, the transformation matrix is calibrated to change the sensor acceleration at the next point to the vehicle acceleration.

$$C_{k(+)} = C_{k-1(+)} (I_{3\times3} + \Omega_k \Delta t)(I_{3\times3} - \Omega_k \Delta t)^{-1} \quad (21)$$

$$C_{k(+)} = (I_{3\times3} + \Omega_{\varepsilon k} \Delta t)(I_{3\times3} - \Omega_{\varepsilon k} \Delta t)^{-1} C_{k(-)} \quad (22)$$

Thus, the compensated transformation matrix is computed using the predicted transformation matrix. Here Ω_(ε,k) is calculated as follows.

$$\Omega_{\varepsilon} = \begin{pmatrix} 0 & -\Delta\omega_{\varepsilon,z} & \Delta\omega_{\varepsilon,y} \\ \Delta\omega_{\varepsilon,z} & 0 & -\Delta\omega_{\varepsilon,x} \\ -\Delta\omega_{\varepsilon,y} & \Delta\omega_{\varepsilon,x} & 0 \end{pmatrix} \quad (23)$$

Experimental Method and Analysis

The experiments verify the effectiveness of the proposed method and evaluate its performance.In this experiment, we used MPU9250 and applied Bluetooth communication using HC-05 to communicate with the above computer. The analysis of the experimental data was also performed using Matlab 2017a. The figure below shows the results of the athletes' velocity measurements using different high-speed cameras and the newly proposed devices (Figure 2).

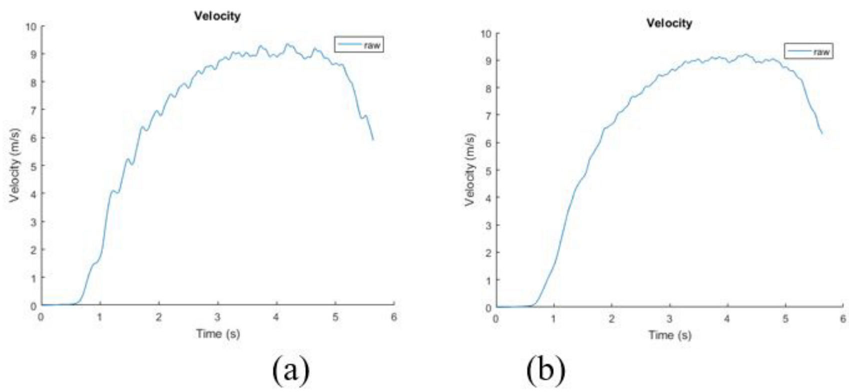

Figure 2: Results using inertial sensors and high-speed cameras

(a) Results using inertial sensors (b) Results using high-speed cameras

It can be seen that the velocity values measured using the high-speed camera and the inertial sensor are similar. In the figure, the constant deviation of the velocity measurements in the method using the inertial sensor is due to the recomputation of the velocity by compensating for the error at the sampling points. The following

Table 1 shows the maximum velocity arrival time and maximum velocities when using the high-speed camera and the inertial sensor.

Table 1: Results of measurements at different ages

measuring mode	A method using high-speed cameras		Method using inertial sensors	
	maximum velocity (ms)	maximum velocity arrival time (s)	maximum velocity (ms)	maximum velocity arrival time (s)
13살	8.12	1.25	8.03	1.39
15살	8.56	1.52	8.27	1.77
17살	8.98	1.73	8.85	1.84

As shown in Table 1, all measurements reached the method using a high-speed camera.

Conclusion

This paper have constructed and validated a Kalman filter to achieve the same effectiveness as the low-cost inertial sensors used in the athlete's motion speed measurement system.In this experiment, we compared the results using a new Kalman filter with an azimuth as the correct measurement and using a high-speed camera. Of course, the accuracy is reduced to a certain degree compared to GPS and other GNSS methods.The advantages of the low cost compared to the system developed by the authors are the high accuracy compared to the cost.

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