Pose estimation by extended Kalman filter using noise covariance matrices based on sensor output
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Abstract
This paper presents an extended Kalman filter for pose estimation using noise covariance matrices based on sensor output. Compact and lightweight nine-axis motion sensors are used for motion analysis in widely various fields such as medical welfare and sports. A nine-axis motion sensor includes a three-axis gyroscope, a three-axis accelerometer, and a three-axis magnetometer. Information obtained from the three sensors is useful for estimating joint angles using the Kalman filter. The extended Kalman filter is used widely for state estimation because it can estimate the status with a small computational load. However, determining the process and observation noise covariance matrices in the extended Kalman filter is complicated. The noise covariance matrices in the extended Kalman filter were found for this study based on the sensor output. Postural change appears in the gyroscope output because the rotational motion of the joints produces human movement. Therefore, the process noise covariance matrix was determined based on the gyroscope output. An observation noise covariance matrix was determined based on the accelerometer and magnetometer output because the two sensors’ outputs were used as observation values. During a laboratory experiment, the lower limb joint angles of three participants were measured using an optical 3D motion analysis system and nine-axis motion sensors while participants were walking. The lower limb joint angles estimated using the extended Kalman filter with noise covariance matrices based on sensor output were generally consistent with results obtained from the optical 3D motion analysis system. Furthermore, the lower limb joint angles were measured using nine-axis motion sensors while participants were running in place for about 100 seconds. The experiment results demonstrated the effectiveness of the proposed method for human pose estimation.

Keywords: Kalman filter, Motion sensor, Noise covariance matrix, Pose estimation, Sensor fusion

Introduction
Compact and lightweight nine-axis motion sensors have been developed through advances in micro-electromechanical systems technology; they have come to be used for motion analysis in widely various fields [1-8]. The nine-axis motion sensors are applicable both indoors and outdoors because of their portability. Several experiments have been conducted to measure the motion of a skier gliding down a slope and jumping off a hill using motion sensors [9,10].

The nine-axis motion sensors include a three-axis gyroscope, a three-axis accelerometer, and a three-axis magnetometer. Using information obtained from the motion sensors, several sensor fusion algorithms have been proposed for pose estimation: as one example, a sensor fusion algorithm that can correct gyroscope drift using information obtained from the other two sensors has been used for human pose estimation during daily activities and exercise [11-13]. Furthermore, a sensor fusion algorithm able to correct the magnetometer output using information obtained from a gyroscope has been used for pose estimation in a variable magnetic field [14,15]. The Kalman filter [16-20] and the complementary filter [21-25] are some pose estimation methods using sensor fusion.

The Kalman filter estimates the system state with a small computational load. Nevertheless, determining the process and observation noise covariance matrices in the Kalman filter is complicated. For a case in which the process and observation noise covariance matrices are time-invariant, the estimation accuracy might decrease if the sensor output noise increases. Moreover, the noise of the sensor output might vary because of long-term measurements. For that reason, adjusting the noise covariance matrices based on sensor output is important.
To estimate the lower limb joint angles for this study, a method was devised to determine the process and observation noise covariance matrices in the extended Kalman filter based on sensor output. The postural change appears in the gyroscope output because the rotational motion of the joints produces human movement. Therefore, the process noise covariance matrix was set based on the gyroscope output. When the accelerometer output increased, the observation noise covariance matrix was set to increase. The observation noise covariance matrix was also set to increase when the magnetometer output drastically changed. During a laboratory experiment, the lower limb joint angles of three participants were measured using an optical 3D motion analysis system and nine-axis motion sensors while the participants were walking. Several studies have demonstrated that an optical 3D motion analysis system measured human movement with high accuracy. Therefore, the system is used for verifying the pose estimation accuracy in widely diverse fields [26-29]. We verified the accuracy of the proposed method by comparing its results to those of an optical 3D motion analysis system. Furthermore, the lower limb joint angles were measured using nine-axis motion sensors while the participants were running in place. Finally, the effectiveness of the proposed method was verified using experiment results.

**Measurement method**

**Definition of roll-pitch-yaw**

The 3D posture of the sensor is represented by the roll angle ($\phi$) around the x-axis, the pitch angle ($\theta$) around the y-axis, and the yaw angle ($\psi$) around the z-axis. The reference coordinate system is a right-handed system with a vertical z-axis. The counterclockwise rotation is defined as positive. The reference coordinate system and the definition of the joint angles are presented in Fig. 1.

**Roll-pitch-yaw calculation**

For this study, Euler angles (roll, pitch, and yaw) were calculated using nine-axis motion sensors. The nine-axis motion sensor (SS-WS1792; Sports Sensing Co., Ltd.) used for this study includes a three-axis gyroscope ($\pm1500$ dps), a three-axis accelerometer ($\pm16$ G), and a three-axis magnetometer ($\pm10$ Gauss). The $38 \times 53 \times 11$ mm sensor weighs 30g.

The initial roll and pitch angles were calculated using the accelerometer output at rest [30,31]. The relation between the acceleration sensor output and the gravitational acceleration in the reference coordinate system is expressed using Eq. (1) because the accelerometer measures only the gravitational acceleration while at rest:

$$i^A = (o^R_i)^T o^A, \quad (i = 1,2,3,4)$$

where

$$i^A = \begin{bmatrix} i_A_z & 0 & 0 \\ 0 & i_A_y & 0 \\ 0 & 0 & i_A_z \end{bmatrix}, \quad o^A = \begin{bmatrix} 0 \\ 0 \\ g \end{bmatrix}.$$  

Therein, $i^A$ denotes the accelerometer output, $o^A$ represents the acceleration in the reference coordinate system, and $g$ stands for gravitational acceleration. For the experiment, sensors 1, 2, 3, and 4 were placed respectively on the waist, left thigh, left shank, and left foot. In addition, the rotational matrix from the sensor coordinate system to the reference system $o^R_i$ is the following:

$$o^R_i = \begin{bmatrix} \cos i^\theta & 0 & -\sin i^\theta & 0 \\ \sin i^\theta & 0 & \cos i^\theta & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$= \begin{bmatrix} \cos i^\theta & 0 & -\sin i^\theta & 0 \\ 0 & 0 & 0 & \cos i^\psi & -\sin i^\psi \\ -\sin i^\theta & 0 & \cos i^\theta & 0 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos i^\psi & -\sin i^\psi \\ 0 & \sin i^\psi & \cos i^\psi \end{bmatrix}.$$  

Then, the accelerometer output $i^A$ is represented by substituting Eq. (2) into Eq. (1) as shown below:
The initial roll and pitch angles using Eq. (3) are:

\[ i\phi_A = \tan^{-1} \frac{i\dot{a}_y}{i\dot{a}_x} \quad (\pi < i\phi_A < \pi) \quad (4) \]

\[ i\theta_A = \tan^{-1} \frac{i\dot{a}_z}{\sqrt{i\dot{a}_x^2 + i\dot{a}_y^2}} \quad (\pi < i\theta_A < \pi) \quad (5) \]

where \( i\dot{a}_x, i\dot{a}_y, \) and \( i\dot{a}_z \) respectively denote the initial roll and pitch.

To correct the yaw angle, calculations require the roll \( i\phi_A \), pitch \( i\theta_A \), and magnetometer output as:

\[
\begin{bmatrix}
i\dot{\psi}_y \\
i\dot{\psi}_z \\
i\dot{\theta}_c
\end{bmatrix} = \begin{bmatrix}
\cos i\phi_A \\
0 \\
-\sin i\phi_A
\end{bmatrix} \begin{bmatrix}
i\dot{\phi}_c \\
i\dot{\theta}_c \\
i\dot{\psi}_c
\end{bmatrix} + \begin{bmatrix}
\dot{c}_{m_x} \\
\dot{c}_{m_y} \\
\dot{c}_{m_z}
\end{bmatrix}
\]

\[
\begin{align*}
i\dot{x}_{t+1} &= iF(i\psi_t, i\dot{\psi}_t) + i\omega_t, \\
i\dot{y}_t &= iH(i\dot{x}_t) + i\nu_t,
\end{align*}
\]

where

\[
iF(x, \omega) = \begin{bmatrix}
i\phi + \sin i\phi \sec i\theta \omega_y \cdot Ts + \cos i\phi \sec i\theta \omega_z \cdot Ts \\
i\theta + \cos i\phi \omega_y \cdot Ts - \sin i\phi \omega_z \cdot Ts \\
i\psi + \cos i\phi \sec i\theta \omega_z \cdot Ts + \sin i\phi \omega_y \cdot Ts
\end{bmatrix},
\]

\[
iH(x) = \begin{bmatrix}
i\dot{\psi}_c \\
i\dot{\phi}_c \\
i\dot{\theta}_c
\end{bmatrix} = \begin{bmatrix}
i\psi_t \\
i\phi_t \\
i\theta_t
\end{bmatrix}
\]

Extended Kalman filter

State-space model

The roll, pitch, and yaw angles of each sensor placed on the lower limb are estimated by the sensor fusion using the extended Kalman filter. The nonlinear state equation was developed using Eq. (9). The nonlinear observation equation was developed using Eq. (7) and the acceleration sensor output. The nonlinear state and observation equations are shown respectively in Eqs. (10) and (11):

\[
i\dot{x}_{t+1} = iF(i\psi_t, i\dot{\psi}_t) + i\omega_t, \\
i\dot{y}_t = iH(i\dot{x}_t) + i\nu_t,
\]

where

\[
iF(x, \omega) = \begin{bmatrix}
i\phi + \sin i\phi \sec i\theta \omega_y \cdot Ts + \cos i\phi \sec i\theta \omega_z \cdot Ts \\
i\theta + \cos i\phi \omega_y \cdot Ts - \sin i\phi \omega_z \cdot Ts \\
i\psi + \cos i\phi \sec i\theta \omega_z \cdot Ts + \sin i\phi \omega_y \cdot Ts
\end{bmatrix},
\]

\[
iH(x) = \begin{bmatrix}
i\dot{\psi}_c \\
i\dot{\phi}_c \\
i\dot{\theta}_c
\end{bmatrix} = \begin{bmatrix}
i\psi_t \\
i\phi_t \\
i\theta_t
\end{bmatrix}
\]
respectively denote the gyroscope outputs for the \( x, y, \) and \( z \) axes. Also, \( iA_{x_i} \), \( iA_{y_i} \), and \( iA_{z_i} \) respectively express the accelerometer output for the \( x, y, \) and \( z \) axes. Therefore, \( i\omega_i \) and \( i\nu_i \) denote white noise.

\[ \text{Yaw angle } i\psi_n, \text{ which was calculated using the magnetometer output, and the accelerometer output were used as the observation values in Eq. (11). Eq. (1) represents the relation between the accelerometer output and gravitational acceleration. Consequently, the yaw angle of the state values was used in Eq. (17) for calculating the likelihood of the represented by Eqs. (10) and (11). Here, Eq. (16) and Eq. (15) are shown below:} \]

\[
\begin{align*}
\phi_i & = iA_{x_i}, \\
i\omega_t & = \frac{\partial iF(\phi_i, i\omega_i)}{\partial \phi_i}, \\
Q_t & = \frac{\partial iH(\phi_i)}{\partial \phi_i}, \\
\end{align*}
\]

\[ \text{where } iQ_t = \begin{bmatrix} i\Omega_{0,t} & 0 & 0 \\ 0 & i\Omega_{\omega,t} & 0 \\ 0 & 0 & i\Omega_{\nu,t}\end{bmatrix}. \]  

\[ i\Omega_{\nu,t} = a\sqrt{i\omega_x^2 + i\omega_y^2 + i\omega_z^2 + b}, \]  

\[ i\Omega_{\omega,t} = \frac{1}{2} \sum_{j=1}^{N} \left( i\log( iB_j^2 + \frac{i\nu_j^2}{i\nu_j}) \right). \]  

**Noise covariance matrices based on sensor output**

The process and observation noise covariance matrices in the extended Kalman filter were determined based on the state-space model dynamics and the sensor noise. The postural change appears in the gyroscope output because the rotational motion of the joints produces human movement. Consequently, the process noise covariance matrix was determined based on the gyroscope output as presented below:

\[ \text{In those equations, } iP \text{ represents the error covariance matrix, } iV \text{ denotes the prediction error matrix, } iB \text{ stands for the prediction error variance matrix, and } iK \text{ denotes the Kalman gain. Therein, } iQ \text{ and } iR \text{ respectively denote the covariance matrices of process noise } i\omega_i \text{ in the nonlinear state equation and observation noise } i\nu_i \text{ in the nonlinear observation equation.} \]
Participants and experiment conditions

Three healthy participants (A, B, and C) were examined during the experiment. Anthropometric data are shown in Table 1. After maintaining the upright posture for about 5 s, the first step that a participant took was with the left foot. They were instructed to walk using a natural stride in time with a metronome (70 bpm). Measurement started simultaneously when a participant started to maintain the upright posture. The measurements finished when the participant placed the right foot flat on the floor during the sixth step. Following an explanation of the purpose and requirements of the study, the participants gave their written informed consent to participate in the study. Study approval was obtained from the Research Ethics Board, Kogakuin University, and National Institute of Technology, Akita College.

During the experiment, kinematic data were collected using an optical 3D motion analysis system (Bonita 10; Vicon Motion Systems Ltd.), two force plates (9286; Kistler Japan Co. Ltd.), and four nine-axis motion sensors in synchronization. The heel strike and toe off were ascertained from force plate data. The sensors were placed on the waist, left thigh, left shank, and left foot using double-sided tape and elastic straps. The sensor positions are presented in Fig. 2. Definitions of the length of the thigh, shank, and foot were referred from reports of earlier research studies.

![Sensor positions and sensor coordinate system.](image)

### Table 1 Anthropometric data

| Participant | Height [m] | Weight [kg] | Age [years] |
|-------------|------------|-------------|-------------|
| A           | 1.78       | 60          | 20          |
| B           | 1.72       | 65          | 20          |
| C           | 1.80       | 56          | 21          |
In the early stance phase and the end of the swing phase, the ankle joint angle obtained from NBS (Only process noise) is much smaller than the result obtained from the optical 3D motion analysis system, whereas the ankle joint angle obtained from NBS (Only observation noise) is generally consistent with the result obtained using the optical 3D motion analysis system. The results indicate that the observation noise covariance matrix based on the gyroscope output contributed to increased accuracy at the early stance phase and at the end of the swing phase. Therefore, the process noise covariance matrix based on the gyroscope output and the observed noise covariance matrix based on the accelerometer and magnetometer output might have contributed to the increased accuracy at different phases.

For knee and hip joint angles, all results show the same tendency. However, NBS (red line) has the smallest RMSE in all results of all three joints. The results show that using both processes of noise covariance matrix based on the gyroscope output and the observed noise covariance matrix based on the accelerometer and magnetometer output might have contributed to increased accuracy. The two noise covariance matrices seem to have influenced one another.

**Running experiment**

Participants and experiment conditions

The nine-axis motion sensors measured lower limb joint angles of the same participants while they were running in place to verify the effectiveness of NBS when continuously capturing data of fast-moving participants. The nine-axis motion sensors were placed in the same positions as those used for the verification experiment. The measurement time was about 100 s. During the experiment, kinematic data were collected using an optical 3D motion analysis system with four nine-axis motion sensors in synchronization. Participants were instructed to run in place in time with a metronome (150 bpm) after maintaining the upright posture for about 5 s. The sampling frequencies of the nine-axis motion sensors and the optical 3D motion analysis system were 100 Hz.

**Results**

Table 4 shows parameters $a$ to $f$ for the running
Table 2  Adjusting parameters of NBS in the walking experiment.

(a) Ankle joint

| Participant | Adjusting parameters | A   | B   | C   | D   | E   | F   |
|-------------|----------------------|-----|-----|-----|-----|-----|-----|
| A           | 0.00001              | 0.1 | 0   | 1   | 0   |
| B           | 0.00001              | 0.1 | 0   | 1   | 0   |
| C           | 0.00001              | 0.1 | 0   | 1   | 0   |

(b) Knee joint

| Participant | Adjusting parameters | A   | B   | C   | D   | E   | F   |
|-------------|----------------------|-----|-----|-----|-----|-----|-----|
| A           | 0.00001              | 0.1 | 0   | 1   | 0   |
| B           | 0.00001              | 0.1 | 0   | 1   | 0   |
| C           | 0.00001              | 0.1 | 0   | 10  | 0   |

(c) Hip joint

| Participant | Adjusting parameters | A   | B   | C   | D   | E   | F   |
|-------------|----------------------|-----|-----|-----|-----|-----|-----|
| A           | 0.00001              | 0.1 | 0   | 1   | 0   |
| B           | 0.00001              | 0.1 | 0   | 1   | 0   |
| C           | 0.00001              | 0.1 | 0   | 10  | 0   |

Fig. 3  Left lower limb joint angles during walking obtained using optical 3D motion analysis system, the extended Kalman filter using NBS, NBS (Only observation noise), NBS (Only process noise), and the extended Kalman filter using CNC (participant A).
The estimated joint angles of participant A are presented in Figs. 4, 5, and 6. In each of Figs. 4–6, panels (a) present results obtained over the entire measurement time. Panels (b) present results obtained between 33 s and 35.5 s from the start of measurements. In each of Figs. 4–6, panels (b) are used for a detailed examination of the results. Black solid curves present results obtained from the optical 3D motion analysis system. Red solid curves present results obtained from NBS. Blue solid curves present results obtained from CNC.

The estimated ankle joint angle using NBS in Fig. 4(a) changes periodically between -25° and 25° over the entire measurement time, which is generally consistent with results obtained using the optical 3D motion analysis system. The estimated ankle joint angle using CNC in Fig. 4(a) changes periodically between -70° and 0° over the entire measurement time. Although the waveform of the result obtained using CNC in Fig. 4(b) is similar to

| Noise covariance matrix | Ankle joint (deg) | Knee joint (deg) | Hip joint (deg) |
|-------------------------|------------------|-----------------|----------------|
| NBS                     | 3.17             | 2.41            | 3.18           |
| NBS (Only process noise)| 4.80             | 3.24            | 3.41           |
| NBS (Only observation noise) | 4.71         | 2.57            | 3.22           |
| CNC                     | 4.88             | 2.54            | 3.24           |

Table 4 Adjusting parameters of NBS in the running experiment.

(a) Ankle joint

| Participant | a     | b  | c  | d  | e   | f  |
|-------------|-------|----|----|----|-----|----|
| A           | 0.1   | 0  | 10 | 0  | 1000| 0  |
| B           | 0.1   | 0  | 10 | 0  | 1000| 0  |
| C           | 0.1   | 0  | 10 | 0  | 1000| 0  |

(b) Knee joint

| Participant | a     | b  | c  | d  | e   | f  |
|-------------|-------|----|----|----|-----|----|
| A           | 0.00001| 0  | 0.1| 0  | 1   | 0  |
| B           | 0.00001| 0  | 100| 0  | 1000| 0  |
| C           | 0.00001| 0  | 100| 0  | 1000| 0  |

(c) Hip joint

| Participant | a     | b  | c  | d  | e   | f  |
|-------------|-------|----|----|----|-----|----|
| A           | 0.1   | 0  | 10 | 0  | 1000| 0  |
| B           | 0.001 | 0  | 10 | 0  | 1000| 0  |
| C           | 0.001 | 0  | 10 | 0  | 1000| 0  |

1 experiment, which were determined to maximize the 16 log-likelihood in Eq. (22). From the running 17 experiment, different parameters were obtained 18 among the joints. In addition, parameters a, c, and e 19 for running measurements tended to be larger than 20 those in the walking measurement. The results 21 indicate that the noise covariance matrices for the 22 running experiment might have had larger values 23 because the process and observation noise can 24 increase if the motion velocity increases. 25 The estimated joint angles of participant A are 26 presented in Figs. 4, 5, and 6. In each of Figs. 4–7 27 measurements, Panels (a) present results obtained over the entire 3.28 time. Panels (b) present results obtained 29 between 33 s and 35.5 s from the start of 30
the result obtained using NBS, the result obtained using CNC is much smaller than that obtained using NBS. Additionally, the waveform of the result obtained using CNC has a larger dorsiflexion peak than that obtained using NBS at about 33.7, 34.4, and 35.2 s.

The estimated knee joint angle obtained using NBS in Fig. 5(a) changes periodically between 20° and 110° over the entire measurement time, which are generally consistent with the results obtained using the optical 3D motion analysis system. Whereas the estimated knee joint angle using CNC in Fig. 5(b) changes periodically between -60° and 0° over the entire measurement time. Although the waveform of the result obtained using CNC in Fig. 5(b) is similar to the result obtained using NBS, the result obtained using CNC is much smaller than that obtained using NBS. Additionally, the waveform of the result obtained using CNC has a smaller flexion peak than that obtained using NBS at about 33.6, 34.4, and 35.2 s.
The hip joint angle estimated using NBS in Fig. 6(a) changes periodically between 10° and 15° over the entire measurement time, which are generally consistent with results obtained using the optical 3D motion analysis system. The estimated knee joint angle using CNC in Fig. 6(a) changes periodically between -35° and -15° over the entire measurement time. Although the waveform of the result obtained using CNC in Fig. 6(b) is similar to the result obtained using NBS, the result obtained using CNC is much smaller than that obtained using NBS. All results obtained for the other two participants showed similar tendencies. The results demonstrated the effectiveness of the extended Kalman filter using NBS.

Conclusions

For this study, a method for ascertaining the process and observation noise covariance matrices in the extended Kalman filter based on sensor output was constructed to estimate the lower limb joint angles. The lower limb joint angles of the three healthy participants during walking and running were estimated using the method. Results yielded the following conclusions.

1. The joint angles obtained from the extended Kalman filter using the process and observation noise covariance matrices based on sensor output were generally consistent with results obtained using the optical 3D motion analysis system in the verification experiment.
2. In the running motion analysis, the results obtained using noise covariance matrices based on sensor output indicated that the estimated joint angles changed periodically within an appropriate range. The results obtained using the constant noise matrices indicated that the estimated joint angles changed abnormally.

Noise covariance matrices based on sensor output can be effective for accurate pose estimation, because noise covariance matrices can be time-variable when continuously capturing human motion with long-term measurements. The proposed methods is expected to be useful for estimating motion in sports and healthcare applications.

Competing interests

The authors declare that they have no competing interests.

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Authors’ Contributions

AS conceived the study and drafted the manuscript. AS and KM carried out all experiments and analyzed the data. YK and SK participated in the research design and sequence alignment. All authors read and approved the final manuscript.

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