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Pose estimation of surgical instrument using sensor data fusion with optical tracker and IMU based on Kalman filter

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Abstract. Tracking system is essential for Image Guided Surgery(IGS). The Optical Tracking Sensor(OTS) has been widely used as tracking system for IGS due to its high accuracy and easy usage. However, OTS has a limit that tracking fails when occlusion of marker occurs. In this paper, sensor fusion with OTS and Inertial Measurement Unit(IMU) is proposed to solve this problem. The proposed algorithm improves the accuracy of tracking system by eliminating scattering error of the sensor and supplements the disadvantages of OTS and IMU through sensor fusion based on Kalman filter. Also, coordinate axis calibration method that improves the accuracy is introduced. The performed experiment verifies the effectualness of the proposed algorithm.

1 Introduction

Minimally Invasive Surgery(MIS) has advantage of less injury to the body during operation, fast recovery, less pain and smaller scar left after surgery [1]. Therefore, MIS is becoming more popular and common. Most IGS are MIS and provides preoperative images such as computerized tomography(CT) and magnetic resonance imaging(MRI), surgical navigation and coordinate information of surgical instruments, patient and surgical robots [2]. To perform IGS, tracking system is required to match the CT image and MRI image with patient or provide pose of surgical instruments and surgical robots and provide surgical navigation. OTS is widely used for tracking system in IGS because of its high accuracy. However, OTS has limit of occlusion. There are previous studies to solve the occlusion problem of OTS using sensor data fusion based on Kalman filter. One of the previous study use sensor data fusion with electromagnetic tracking system and IMU[3] and another one use sensor data fusion with OTS and IMU [4, 5]. Sensor fusion has an advantage for it can cover the disadvantage of each other. OTS and IMU has advantages and disadvantages as shown in table 1. Using sensor data fusion with OTS and IMU, the system can keep high accuracy and also solve occlusion problem. Therefore in this paper, an algorithm using sensor data fusion with OTS and IMU is proposed. The previous study of sensor fusion using OTS and IMU estimates the pose of the marker using only the IMU data when occlusion occurs. However this method has drift error caused by DC bias of IMU and therefore it is hard to trust the estimated data after 1 second of occlusion.

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Table 1. Characteristics of OTS and IMU.

	Advantage	Disadvantage
OTS	- High accuracy - Easy Usage	- Limited measuring volume - Occlusion - Low measurement freq.
IMU	- Unlimited measuring volume - High measurement freq.	- Low accuracy - Drift error(DC bias)

The purpose of the proposed algorithm is to estimate reliable pose data of the marker even 3 to 5 seconds after marker occlusion occurs.

The importance of pose estimation is because when a marker is attached to a surgical instrument, the estimation error tip of surgical instrument is influenced by pose more than position. Also, some IGS that inserts surgical instrument to patient body through trocar or multi-instrument port are mostly performed by pose variation of surgical instrument. Therefore, decreasing the error of pose estimation is very important.

2 Methods

In previous studies using sensor fusion with OTS and IMU, calibration was performed between OTS coordinate and earth coordinate. Therefore, the position and pose of the OTS had to be fixed after calibration. However this is inconvenient because when using the OTS in surgery, calibration has to be done after positioning the OTS in the operation room. In this paper, to solve this inconvenience, one IMU is fixed to the OTS and another IMU is fixed to the marker as shown in Figure 1. This allows displacement of OTS after calibration.

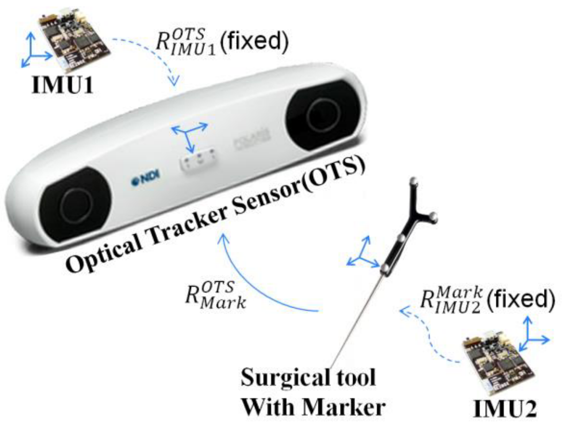

Figure 1. Hardware setup of proposed system.

R_{IMU1}^{OTS} and R_{Mark}^{OTS} are rotation matrix to OTS frame from IMU1 and Marker frame respectively. R_{IMU2}^{Mark} is rotation matrix from IMU2 frame to Marker frame. The proposed calibration can be divided to two process. One process is to match coordinates between sensors and another process is to eliminate DC bias of IMU to improve the accuracy of pose estimation. After calibration, a pose estimation using sensor data fusion with OTS and IMU based on Kalman filter is performed. The diagram is shown in Figure 2.

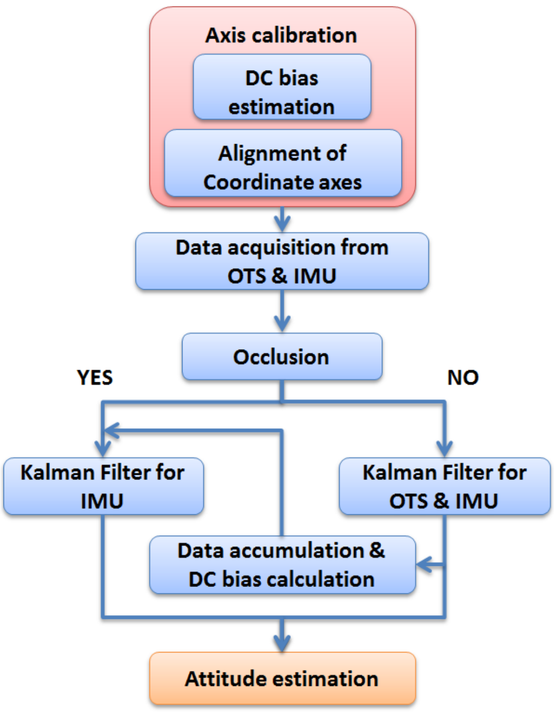

Figure 2. Diagram of proposed fusion system.

2.1 Calibration

2.1.1 Accelerometer DC bias estimation

IMU has DC bias due to electronic characteristic of semiconductor, and this degrades the performance of sensing. To eliminate the accelerometer DC bias, we defined the DC bias separately along three axis of coordinate. In stable state, the output of accelerometer includes the DC bias and acceleration of gravity. The relation of the output of accelerometer and the DC bias is defined as Eq. (1).

$$\sqrt{(a_x - a_{b\_x})^2 + (a_y - a_{b\_y})^2 + (a_z - a_{b\_z})^2} = g_0 \quad (1)$$

g_0 is standard gravity, a_x, a_y, a_z are the output of the accelerometer and a_{b_x}, a_{b_y}, a_{b_z} are the DC bias along x-,y- and z-axis. Eq. (1) is a hemisphere model and DC bias is the center of the hemisphere. Therefore, the accelerometer DC bias estimation can be done by calculating the center of the hemisphere.

2.1.2 Alignment of coordinate axes

The alignment of coordinate axis is done by using the fact that gravity applied to IMU1 and IMU2 is equal. Converting this relation to the coordinate of OTS is shown in Eq. (2).

$$R_{IMU1}^{OTS} \cdot a_{IMU1} - R_{Mark}^{OTS} \cdot R_{IMU2}^{Mark} \cdot a_{IMU2} = 0 \quad (2)$$

a_{IMU1} and a_{IMU2} are the gravity acceleration obtained by eliminating the accelerometer DC bias from the output of IMU in stable state. R_{IMU1}^{OTS} and R_{IMU2}^{Mark} are the output parameter for alignment of coordinate axis and can be calculated using Eq. (2).

2.2 Sensor data fusion model

The purpose of Kalman filter is to eliminate white gaussian noise [6]. Also, Kalman filter is appropriate to apply on sensor data fusion because it is easy to define relations between different physical quantities. Kalman filter based sensor data fusion reduces scattering error and derives optimum output through fusion.

2.2.1 Kalman filter model

Kalman filter includes prediction process and estimation process. The Kalman filter process of sensor data fusion is shown in Figure 3 [7]. The prediction process in Figure 3 is the same as that of traditional Kalman filter. But the estimation process is different because of using two sensors.

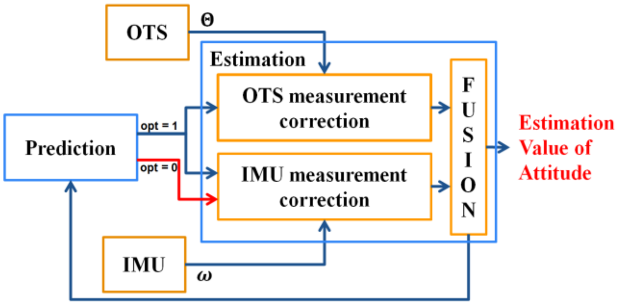

Figure 3. A structure of sensor data fusion model. When occlusion occurs, opt = 1. When occlusion does not occurs, opt = 0.

Eq. (3) and Eq. (4) are equations for estimation process.

$$\mathrm{K_k} = P_k^- H^T (HP_k^- H^T + R)^{-1} \tag{3}$$

$$\hat{x}_k = \hat{x}_k^- + K_k(z_k - H\hat{x}_k^-) \tag{4}$$

Measurement matrix H represents the physical relationship between OTS, IMU and prediction values. When occlusion occurs, the estimation is done by only the IMU measurement correction process, exclusive of the OTS measurement correction process. In this case the H matrix is adjusted to neglect the parameter of OTS. Measurement error covariance matrix R represents the reliability of measurement values. For the accuracy of the OTS is higher than that of IMU, the relibility of the OTS is set higher than that of IMU. Then the effect of the drift error caused by IMU becomes negligible and therefore the system can obtain better estimation result than the IMU. Also, by applying Kalman filter with the measurement frequency of the IMU, the measurement frequency of the fusion system becomes higher than that of the OTS. Details of Kalman filter and Kalman filter modeling for sensor data fusion are explained in reference [7, 8].

2.2.2 Gyro sensor DC bias estimation for tracking

The DC bias of IMU differs due to change of temperature and external shock. Generally the DC bias fitting according to the temperature is used. However, for temerature is not the only cause of DC bias, we update the DC bias continuously during tracking to minimize drift error. The equation for DC bias updating is shown in Eq. (5).

$$\Theta_\mathrm{t} = \Theta_\mathrm{t-1} + \Delta t C_{ref} \cdot R_{Mark}^{OTS} \cdot R_{IMU2}^{Mark} \cdot (\omega_{IMU2} - \omega_{bias}) \tag{5}$$

Θ is the pose estimation value, Δt is the sensing time, C_{ref} is the matrix that converts angular velocity to rate of change of the euler angles, ω_{IMU2} is the angular velocity of IMU2, ω_{bias} is the desired DC bias. The DC bias is updated using accumulated data during nonoccurrence of occlusion.

3 Experimental results

The devices used for experiment are as follows. Polaris vicar(accuracy : 0.12°, sensing freq.: 20Hz) of NDI is used for OTS. EBIMU-9DOFV2(accuracy : 0.05°/s, sensing freq.: 100Hz) of E2Box Inc. is used for IMU. Rotation motor stage DT-65N(accuracy : 0.025°) of PI miCos GmbH is used to change the pose of the IMU attached marker.

3.1. Calibration result

Calibration process includes elimination of DC bias of accelerometer and alignment of coordinate axes. For elimination of DC bias of accelerometer, more than 4 data obtained with different stable pose of IMU are required to solve Eq. (1). For alignment of coordinate axes, more than 6 data obtained with different stable pose are required to solve Eq. (2).

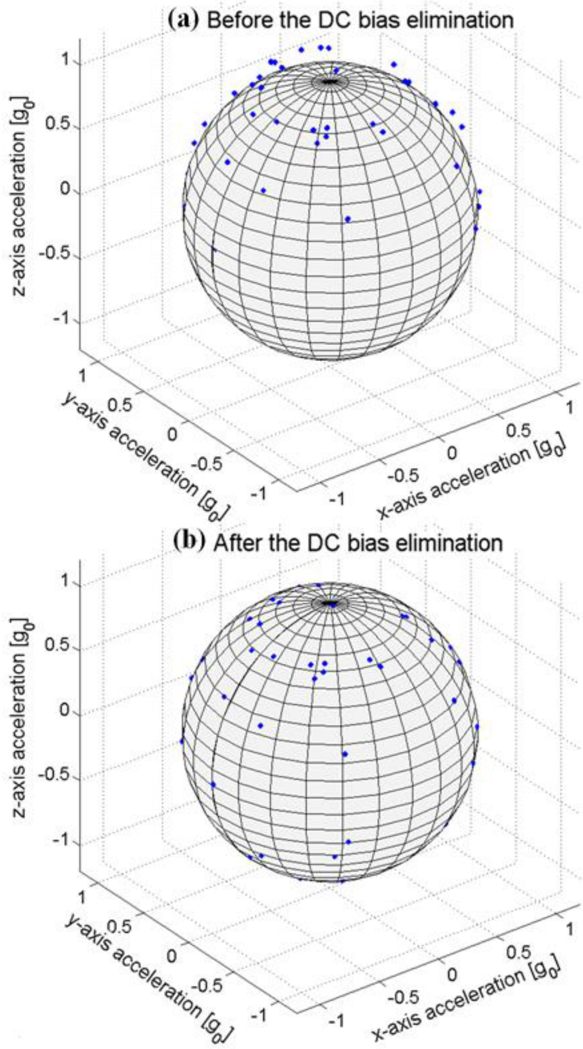

Figure 4. (a) The output of accelerometer expressed in Cartesian coordinate before DC bias elimination. (b) The output of accelerometer expressed in Cartesian coordinate after DC bias elimination.

Table 2. RMS error of accelerometer before DC bias elimination and after DC bias elimination.

	Before	After
RMS error	0.0695	0.0091

But sufficient number of data should be used for calibration to guarantee the accuracy of the calibration. In this experiment, 60 number of data achieved with different stable pose are used for calibration.
According to Eq.(1), if there is no DC bias, the output of the accelerometer should be on a sphere with radius $1g_0$. Figure 4. (a) shows that the output of the IMU includes DC bias for they are not on the sphere with radius $1g_0$. Figure 4. (b) shows that the DC bias is successfully eliminated for the data are on the sphere with radius $1g_0$. Table 2 shows the RMS error of accelerometer before and after DC bias elimination. Table 3 shows the error of coordinate alignment between IMU1 and IMU2 using Eq. (2).

Table 3. Residual gravity between two IMU after alignment of coordinate axes.

	x-axis	y-axis	z-axis
Mean [g_0]	0.0016	0.0017	-0.0029
RMS error [g_0]	0.0071	0.0074	0.0112

3.2 Pose estimation results

As mentioned in section 2.2.2, the proposed method of pose estimation improves the accuracy by updating the DC bias of gyro sensor in real time using accumulated data during occlusion does not occur.
An experiment was done to figure out the sufficient number of accumulated data for updating DC bias of gyro sensor. A rotation motor stage was moved by a sinusoidal signal with amplitude of 10° and 5 second period. The frequency of pose estimation is 100Hz which is the same as IMU. To compare the result with different number of accumulated data, the data was accumulated for 5 second, 10 second and 20 second assuming that occlusion occurred after that time. The result is shown in Figure 5.

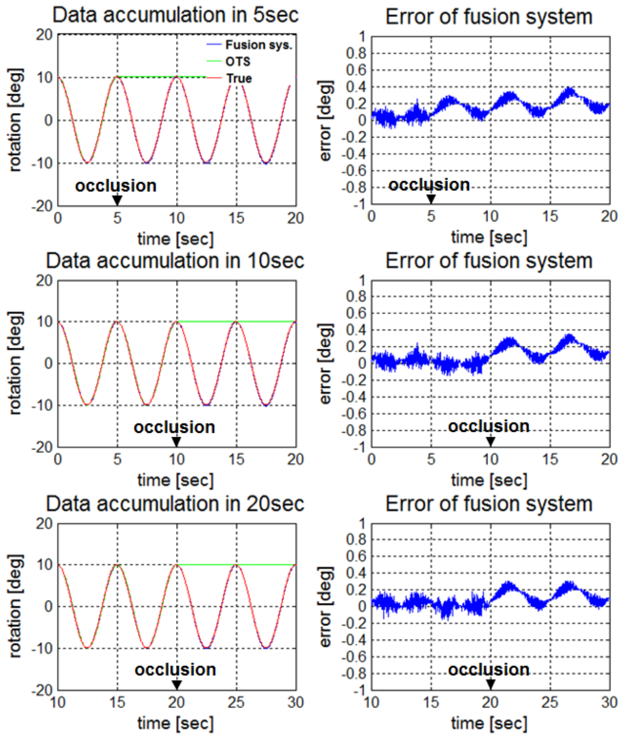

Figure 5. DC bias estimation using accumulated data during different time.

As shown in Figure 5, if occlusion occurs the OTS can not track the marker but the proposed fusion system can keep on tracking using the data accumulated before occlusion. However there is some divergence using data accumulated for 5 second compared to the result using data accumulated for 10 second and 20 second. Table 4 shows the rate of divergence according to the data accumulation time.

Table 4. Rate of divergence according to data accumulation time

Accumulated time	5sec	10sec	20sec
Divergence rate [°/s]	0.018	0.0045	0.0033

The result shows that the divergence rate using data accumulated for 5 second is also smaller than that of the OTS error which is 0.1°. Although for more precision, 10 second of data accumulation would be suitable for the accuracy increases 4 times than that of 5 second data accumulation.
Now, another experiment was performed to verify pose estimation when the IMU moves after occlusion. The occlusion occured after 10 second data accumulation. The IMU was attached on the rotation motor stage and the rotation motor stage moved with a sinusoidal signal input with 10° amplitude and 2 second, 4 seocnd and 6 second period. The result is shown in Figure 6.

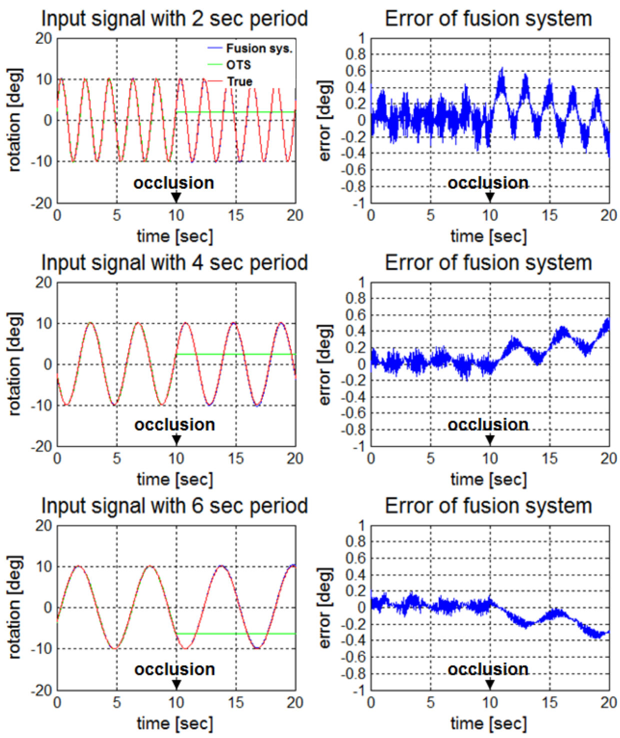

Figure 6. Divergence of pose estimation after occlusion occurs with different period of sinusoidal movement.

Table 5 shows the divergence rate according to the period of sinusiodal movement and it is shown that the divergence of pose estimation increases when the IMU moves faster.

Table 5. Divergence of pose estimation with different period of sinusoidal movement.

Period	2sec	4sec	6sec
Divergence rate [°/s]	0.0193	0.0168	0.0036

4 Conclusion

In this paper, an algorithm that can solve occlusion problem using sensor data fusion with OTS and IMU is proposed. As shown in table 5, when occlusion occurs, maximum error of pose estimation is 0.0193°/s. This means that if the length of the surgical instrument is 300mm and occlusion occurred for 5 second, the estimation error of the tip of the surgical instrument is 0.5mm. This result shows that the proposed calibration method and DC bias elimination algorithm for sensor data fusion is effective. For further work, DC bias elimination algorithm for faster movement of IMU should be done. Also, an accurate position estimation algorithm using IMU should be studied.

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