Journal of Industrial Information Technology and Application *ISSN(Online): 2586-0852*
Vol.6 No.2

Optimal Shoulder Joint Position Estimation Using Extended Kalman Filter based SLAM

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Abstract. Skeleton tracking algorithms[1] can be applied in various fields such as rehabilitation, motion capture, motion recognition, and sports. Recently, skeleton tracking algorithms based on RGB-D cameras such as Microsoft Azure Kinect and Intel RealSense cameras have been commercialized. In addition, it is applied in various fields such as motion capture, sports, and exercise, etc. However, the limitations of RGB-D camera-based skeleton tracking algorithms are also clear. Even if other drawbacks are excluded, still it is a clear limitation that it is difficult to make accurate measurements. Nevertheless, RGB-D-based skeleton tracking algorithms are considered to have great market potential thanks to their universal appeal that anyone can use them easily. This paper proposes a new optimization system using sensor fusion of RGB-D cameras and optical tracking systems to compensate for the shortcomings of RGB-D camera-based skeleton tracking algorithms. RGB-D type skeleton tracking algorithms used Nuitrack SDK[2], and optical tracking system (Skadi, Digitrack Inc., Daegu, Korea)[3] is used as marker based tracking system. The Extended Kalman Filter SLAM algorithm[4] was applied as a new optimization system, and segment *length* was used as mapping data considering that segment length was a value that did not change. A micro Lie group theory was applied to calculate the jacobian[5] considering the linear velocity and angular velocity of segment on 3D coordinate. This result was verified using a multi-joint human body mannequin model. As a result of the simulation, the accuracy of this algorithm for segment length prediction was improved and the accuracy of location prediction was also improved compared to when using Nuitrack SDK, a commercial skeleton tracking algorithm. In particular, due to the feature of the RGB-D camera-based skeleton tracking algorithm, the problem of outliers has also improved.

Keywords; Skeleton tracking; Sensor Fusion; Extended Kalman Filter; SLAM.

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Received: Jan 12, 2022; Accepted: Feb 1, 2022; Published: Jun 30, 2022

1. Introduction

Since optical marker-based motion measurement systems can measure accurately, they have been applied to various fields such as movies, medical care, and sports, etc. However, the low affordability and being uncomfortable for anyone have been a major obstacle to the popularization of marker-based motion measurement systems. As an alternative, the use of motion measurement systems using RGB-D sensors(Kinect, realsense, etc) has recently been widely used. Above all, it is very attractive for anyone who can easily use it at anywhere and can be applied to various fields in conjunction with mobile phones. However, the limitation of RGB-D sensor is clear, due to the nature of RGB-D sensors, accuracy/precision is low, so there is a limit to applying it to fields that require a higher level of accuracy/precision.

In this paper, we introduce an optical marker and RGB-D sensor tracking system and a method of probabilistic estimation of joint position by applying the Simultaneous localization and mapping algorithm. The minimum number of markers were used to increase usability and increase accuracy/precision, enabling quantitative evaluation of each joint and segment movement. In particular, the elderly can evaluate their physical characteristics with simple movements, and it is expected that more effective exercise ability evaluation and rehabilitation will be possible if used for exercise/rehabilitation.

2. Method

For probabilistic estimation of shoulder joints, the EKF SLAM algorithm using lie groups was applied. In this model, markers were attached to both wrist joints, and markers were additionally attached to measure rotation at any position of the upper arm(Fig.1). Markers on the shoulders were attached for verification. Due to anatomical constraint, the more arm action Mannequin made, the higher the length estimate value of the segment was probabilistic. The system modeling equation of Upper extremity is as follows (1).

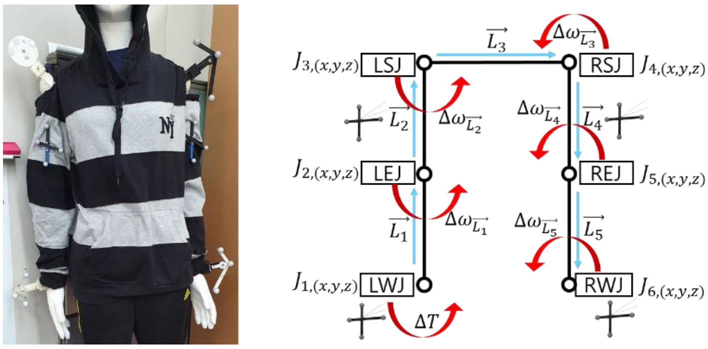

Figure 1 The appearance of attaching an optical marker to a mannequin (left) and the figure schematically illustrating it (right). The action of the upper extremity is expressed by SO (3) and SE (3), and eventually can be expressed by a 5-joint link motion.

$$
\begin{aligned}
J_1^i &= J_1^{i-1} + \Delta T_{J_1}^i \\
J_2^i &= J_1^{i-1} + \Delta T_{J_1}^i + \left(skew\left(\omega_{L_1}^i\right)\right)\left(\overrightarrow{L_1}\right) \\
J_3^i &= J_1^{i-1} + \Delta T_{J_1}^i + \left(I(3) + skew\left(\omega_{L_2}^i\right)\right)\left(\textstyle\sum_{j=1}^{2}\overrightarrow{L_j}\right)\text{-}skew\left(\omega_{L_2}^i\right)\left(\overrightarrow{L_1}\right) \\
J_4^i &= J_1^{i-1} + \Delta T_{J_1}^i + \left(I(3) + skew\left(\omega_{L_3}^i\right)\right)\left(\textstyle\sum_{j=1}^{3}\overrightarrow{L_j}\right)\text{-}skew\left(\omega_{L_3}^i\right)\left(\textstyle\sum_{j=1}^{2}\overrightarrow{L_j}\right) \\
J_5^i &= J_1^{i-1} + \Delta T_{J_1}^i + \left(I(3) + skew\left(\omega_{L_4}^i\right)\right)\left(\textstyle\sum_{j=1}^{4}\overrightarrow{L_j}\right)\text{-}skew\left(\omega_{L_4}^i\right)\left(\textstyle\sum_{j=1}^{3}\overrightarrow{L_j}\right) \\
J_6^i &= J_1^{i-1} + \Delta T_{J_1}^i + \left(I(3) + skew\left(\omega_{L_5}^i\right)\right)\left(\textstyle\sum_{j=1}^{5}\overrightarrow{L_j}\right)\text{-}skew\left(\omega_{L_5}^i\right)\left(\textstyle\sum_{j=1}^{4}\overrightarrow{L_j}\right) \qquad (1)
\end{aligned}
$$

Where $J_1^i \dots J_6^i$ were left wrist, elbow, shoulder and right shoulder, elbow, wrist 3d positions. $\Delta T_{J_1}^i$ is the translation of left wrist and $\omega_{L_1}^i$ is angular velocity of segment $\overrightarrow{L_1}$. Covariance matrix is as follows (2)

$$
\Sigma_0(Covariance\ Matrix) =
\begin{pmatrix}
\Sigma_{J_{1,p}J_{1,p}} & \Sigma_{J_{1,p}\omega_1} & \Sigma_{J_{1,p}T_1} & & \Sigma_{J_{1,p}J_{6,p}} & \Sigma_{J_{1,p}\omega_6} & \Sigma_{J_{1,p}T_6} \\
\Sigma_{\omega_1 J_{1,p}} & \Sigma_{\omega_1\omega_1} & \Sigma_{\omega_1 T_1} & \cdots & \Sigma_{\omega_1 J_{6,p}} & \Sigma_{\omega_1\omega_6} & \Sigma_{\omega_1 T_6} \\
\Sigma_{T_1 J_{1,p}} & \Sigma_{T_1\omega_1} & \Sigma_{T_1T_1} & & \Sigma_{T_1 J_{6,p}} & \Sigma_{T_1\omega_6} & \Sigma_{T_1T_6} \\
 & \vdots & & \ddots & & \vdots & \\
\Sigma_{J_{6,p}J_{1,p}} & \Sigma_{J_{6,p}\omega_1} & \Sigma_{J_{6,l}T_1} & & \Sigma_{J_{6,p}J_{6,p}} & \Sigma_{J_{6,p}\omega_6} & \Sigma_{J_{6,p}T_6} \\
\Sigma_{\omega_6 J_{1,p}} & \Sigma_{\omega_6\omega_1} & \Sigma_{\omega_6 T_1} & \cdots & \Sigma_{\omega_6 J_{6,p}} & \Sigma_{\omega_6\omega_6} & \Sigma_{\omega_6 T_6} \\
\Sigma_{T_6 J_{1,p}} & \Sigma_{T_6\omega_1} & \Sigma_{T_6T_1} & & \Sigma_{T_6 J_{6,p}} & \Sigma_{T_6\omega_6} & \Sigma_{T_6T_6}
\end{pmatrix} (2)
$$

Covariance matrix shows the Probabilistic distribution of joint position and other term like angular velocity, linear velocity and translation.

3. Result and Conclusion

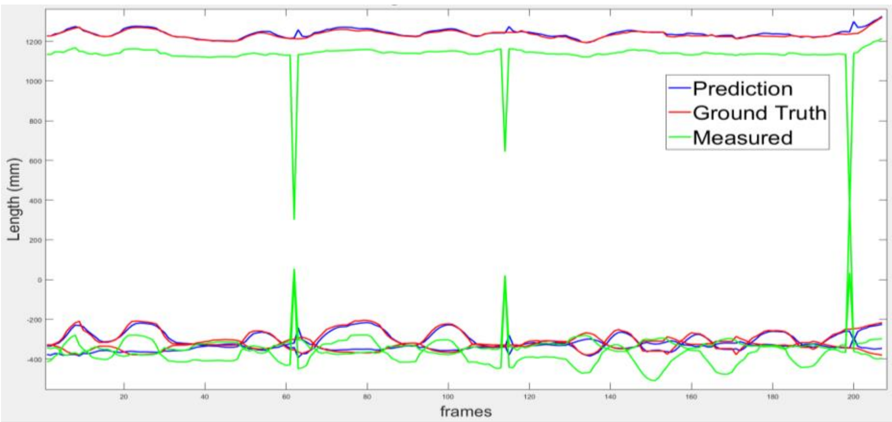

Figure 2 The result of the right shoulder 3d position done by the prediction of EKF SLAM, Digitrack optical tracking system(Ground truth) and Nuitrack commercial SW(measured).

After the prediction by EKFSLAM (fig. 2), it can be seen that the estimated shoulder joint position (blue line) using the EKF SLAM algorithm fits well with the ground truth value (red). This estimates the elbow joint position through the estimated wrist length value based on the left wrist position, and the estimated position obtains the rotation value through the estimated upper arm length value and the marker attached to the upper arm to estimate the shoulder position. In the Nuitrack commercial SW, outliers may occur depending on the camera angle of view, lighting state, and location of the target, and can also be checked with a graph (fig. 2). On the other hand, it can be seen that the prediction value has a very small error compared to Nuitrack's outlier. For the next step, we are planning to measure the hip joint position of lower extremities and will develop a universal motion tracking system by developing easy-to-wear markers.

Acknowledgment

This study was supported by the Translational R&D Program on Smart Rehabilitation 308 Exercises (#TRSRE-MD02), National Rehabilitation Center, Ministry of Health and Welfare, Korea. This work was partially supported by the DGIST R&D program of the Ministry of Science and ICT of KOREA. (21-DPIC-14, 21-DPIC-12). This research project was partially supported by The Sports Promotion Fund of Seoul Olympic Sports Promotion Foundation From Ministry of Culture, Sports and Tourism.

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