Intelligent Equipment and Special Robots
Q. Zhang (Ed.)

doi:10.3233/ATDE240263

Research on Human Joint Motion Attitude Capture System Based on Inertial Sensor

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Abstract. This manuscript introduces a novel framework and algorithm that leverages inertial sensors to capture and optimize data on human joint motion posture, thereby enhancing the accuracy and stability of contemporary motion capture technology. By wirelessly transmitting nine-axis motion data from joint-worn inertial sensor nodes to a host computer, real-time visualization of motion attitude data is achieved through software. Moreover, the acquired data is effectively denoised through a two-stage extended Kalman filter algorithm. Subsequently, the feasibility of capturing motion attitude using the inertial nodes, as well as the effectiveness of the proposed algorithm, is empirically validated through single-node experiments, substantially elevating the overall stability of the system.

Keywords. Motion capture; Inertial sensor; Extended Kalman filter

1. Introduction

The detection of human body posture data entails the capture and digitization of human motion information using computational devices[1]. Thereafter, this data can be presented through diverse means, such as posture calculation. The precision, velocity, and steadfastness of posture data are of utmost importance in evaluating the efficacy of motion capture technology. The progressions in Micro Electro Mechanical Systems (MEMS) technology have paved the way for wearable motion capture systems that are characterized by enhanced comfort, convenience, and affordability, while concurrently exhibiting elevated data precision.

Optical motion capture is limited by factors such as light field and expensive optical cameras[2], while inertial motion capture offers advantages. Zhao et al.[3] proposed a lightweight and highly precise wearable human motion capture system based on inertial sensors. However, the initial position and attitude angle may not be very accurate during the wearing process. Liu et al.[4] developed a motion capture wearable device that accurately measures the three-dimensional motion velocity of human limbs during long-term motion using integral free velocity detection. Zhao et al.[5] introduced a quantitative

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analysis and evaluation method for monitoring the rehabilitation process of patients' walking ability based on inertial measurement units and hemiplegic gait. Punchihewa et al.[6] demonstrated the use of inertial measurement units to evaluate the coordination of trunk and hand movements during baseball batting, emphasizing the effectiveness of high sampling rates in inertial sensors.

This paper introduces a wearable system for acquiring human posture data using the Inertial Measurement Unit (IMU). The system consists of 16 wearable nodes for data acquisition. A two-stage Extended Kalman Filter (EKF) algorithm is used to improve the accuracy and stability of attitude measurements by correcting the gyroscope data with the accelerometer and magnetometer. Experimental results confirm the feasibility of the node in capturing attitude data and validate the reliability of the algorithm. Additionally, considerations for enhancing wearable comfort while managing costs are discussed.

2. Overall scheme of the system

The designed inertial motion capture system consists of three main modules: data acquisition, data transmission, and data processing[7]. The data acquisition module comprises 16 acquisition nodes, as depicted in Fig.1, where each node is equipped with an MPU9250 nine-axis inertial sensor and an ESP32 main control chip. Bluetooth wireless transmission is utilized for sending the acquired attitude data to the host computer. The data processing module performs attitude correction, calculation, and filtering, and displays real-time attitude information. The overall system structure is illustrated in Fig.2.

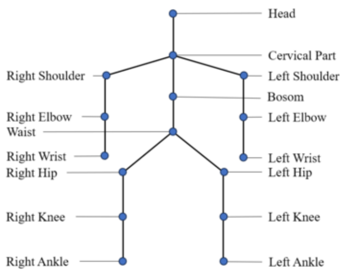

Figure 1. Installation position of inertial node

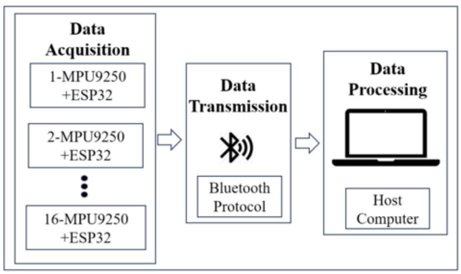

Figure 2. Overall system structure diagram

3. The overall implementation of human posture capture system

3.1. System hardware principle

This paper utilizes the MPU9250 nine-axis inertial sensor module, which includes the MPU6050 six-axis sensor for collecting three-axis acceleration and angular velocity data, as well as the built-in AK8963 magnetometer for collecting three-axis magnetic data.

Each data acquisition node is composed of MPU9250 module and ESP32-DevKitC main control module. ESP32 has built-in low-power BLE Bluetooth data transmission capability. Using BLE Bluetooth to connect with the host computer can greatly reduce the power loss of the system. Each data acquisition node does not interfere with each other, is not connected, and communicates with the host computer alone. The hardware framework of a single node is shown in Fig.3.

3.2. System algorithm implementation

Compared to other data fusion algorithms like complementary filtering[8], the EKF offers higher accuracy in attitude calculation[9]. The commonly used EKF algorithm is typically a one-stage process that involves extensive calculations for attitude estimation. To address this, the two-stage extended Kalman filter algorithm is proposed in this paper to reduce computational requirements, shorten operation time, and enhance calculation efficiency. The two-stage extended Kalman filter model is illustrated in Fig.4, where in the first stage updates the initial estimated roll and pitch angles of the gyroscope using the accelerometer, while the second stage updates the yaw angle using the magnetometer.

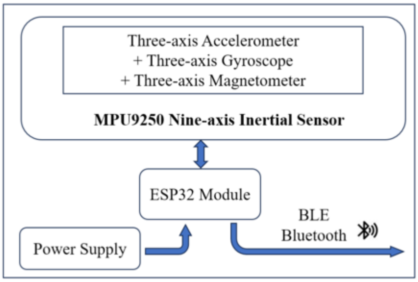

Figure 3. Data acquisition node hardware framework

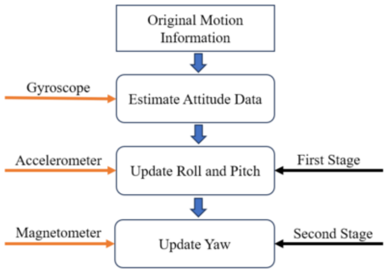

Figure 4. Two-stage extended Kalman filter model

The attitude calculation method uses the quaternion method[10], the calculation amount is smaller than the direction cosine method, and the ' singularity ' phenomenon of the euler angle method is avoided. The algorithm is simple and easy to operate[11]. The quaternion $\boldsymbol{q}=(q_0,q_1,q_2,q_3)^T$ is used as the state vector. In the prediction process, the state transition matrices $\boldsymbol{A}_k$ and $\boldsymbol{B}_k$ are calculated from the data obtained by the gyroscope. The system time transfer equation $\hat{\boldsymbol{q}}_k^-$ of prior estimation is established by the gyroscope and the quaternion differential equation :

$$\hat{\boldsymbol{q}}_k^- = \boldsymbol{A}_k \hat{\boldsymbol{q}}_{k-1} + \boldsymbol{B}_k \boldsymbol{u}_{k-1} \tag{1}$$

In the formula, $\hat{\boldsymbol{q}}_{k-1}$ represents the quaternion representation equation estimated by the gyroscope at the previous moment, and $\boldsymbol{u}_{k-1}$ is the process noise at the previous moment. First, compute the priori error covariance matrix $\boldsymbol{P}_k^-$ as follows :

$$\boldsymbol{P}_k^- = \boldsymbol{A}_k \boldsymbol{P}_{k-1} \boldsymbol{A}_k^T + \boldsymbol{Q}_k \tag{2}$$

In the formula, $\boldsymbol{Q}_k$ is the process noise covariance matrix, which represents the gyroscope noise and other error sources of the gyroscope[12]. Calculate the Kalman gain $\boldsymbol{K}_{k1}$ of the first-stage filter :

$$\boldsymbol{K}_{k1} = \boldsymbol{P}_k^- \boldsymbol{H}_{k1}^T (\boldsymbol{H}_{k1} \boldsymbol{P}_k^- \boldsymbol{H}_{k1}^T + \boldsymbol{R}_{k1})^{-1} \tag{3}$$

In the formula, $\boldsymbol{H}_{k1}$ is the observation matrix after linearization of the system by the first stage extended Kalman filter, and $\boldsymbol{R}_{k1}$ is the accelerometer noise. The first-stage filter uses the accelerometer measured $\boldsymbol{G}_k = (a_x, a_y, a_z)^T$ as the observation variable to calculate the posterior estimation system time transfer equation $\hat{\boldsymbol{q}}_k$:

$$\hat{\boldsymbol{q}}_k = \hat{\boldsymbol{q}}_k^- + \boldsymbol{K}_{k1} (\boldsymbol{G}_k - \boldsymbol{H}_{k1} \hat{\boldsymbol{q}}_k^-) \tag{4}$$

The first level filter update error covariance matrix :

$$\boldsymbol{P}_k = (\boldsymbol{I} - \boldsymbol{K}_{k1} \boldsymbol{H}_{k1}) \boldsymbol{P}_k^- \tag{5}$$

The next step is to start the second-stage filtering and calculate the Kalman gain $\boldsymbol{K}_{k2}$ of the second-stage filtering :

$$\boldsymbol{K}_{k2} = \boldsymbol{P}_k^- \boldsymbol{H}_{k2}^T (\boldsymbol{H}_{k2} \boldsymbol{P}_k^- \boldsymbol{H}_{k2}^T + \boldsymbol{R}_{k2})^{-1} \tag{6}$$

In the formula, $\boldsymbol{H}_{k2}$ is the observation matrix after linearization of the system by the second-level extended Kalman filter, and $\boldsymbol{R}_{k2}$ is the magnetometer noise. In the correction process, the second-stage filter uses the magnetometer to measure $\boldsymbol{M}_k = (m_x, m_y, m_z)^T$ as the observation variable, and calculates the posterior system time transfer equation $\boldsymbol{q}_k$:

$$\boldsymbol{q}_k = \boldsymbol{q}_k^- + \boldsymbol{K}_{k2} (\boldsymbol{M}_k - \boldsymbol{H}_{k2} \boldsymbol{q}_k^-) \tag{7}$$

Update the error covariance matrix again :

$$\boldsymbol{P}_k = (\boldsymbol{I} - \boldsymbol{K}_{k2} \boldsymbol{H}_{k2}) \boldsymbol{P}_k^- \tag{8}$$

3.3. System software implementation

This study employs wireless data transmission to establish parallel connections between nodes and facilitate independent communication with the host computer, ensuring minimal disruption to human body movement. Commonly utilized wireless data transmission methods encompass WIFI, Bluetooth, Zigbee, and related technologies. Bluetooth transmission surpasses WIFI and Zigbee in terms of its swift transmission speed, low power consumption, minimal latency, and ability to connect multiple devices simultaneously without interruptions. When compared to conventional Bluetooth, the low power BLE Bluetooth notably reduces power consumption, significantly enhancing the operational lifespan of data acquisition nodes. The program flow of BLE Bluetooth for data transmission is shown in Fig.5.

The inertial data receiving host computer software is implemented in the MATLAB environment. The inertial data sent by ESP32 is obtained by establishing a BLE Bluetooth receiving node, and then processed and displayed directly. The program flow is shown in Fig.6.

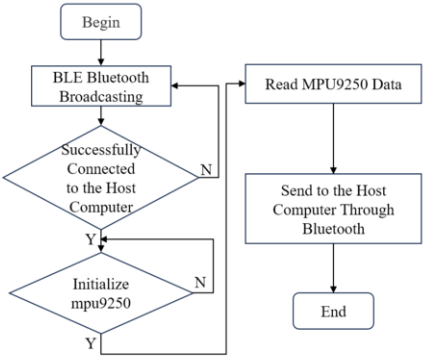

Figure 5. Data acquisition node program flow

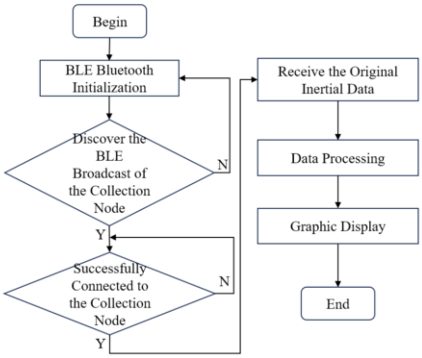

Figure 6. Data receiving node program flow

4. Experimental result analysis

In order to verify the feasibility of the inertial attitude data acquisition system and the effectiveness of the algorithm, a single inertial data acquisition node is used for experiments. In the experiment, the nodes rotate along the Z-axis, Y-axis and X-axis respectively. The original data and filtered data of yaw angle, pitch angle and roll angle are shown in Fig.7, Fig.8 and Fig.9, respectively.

The experimental results demonstrate that the two-stage extended Kalman filter improves the stability of the attitude angle data compared to the original data. Particularly, in the yaw angle experiment, the noise on the horizontal plane significantly disturbs the stationary yaw angle data, but the filtering greatly enhances the stability. The impact of the filter on the pitch angle and roll angle is less prominent during stationary conditions, but the data becomes more stable during motion. Consequently, the attitude data acquisition system effectively detects and improves the stability of the movement's attitude data using the two-stage extended Kalman filter.

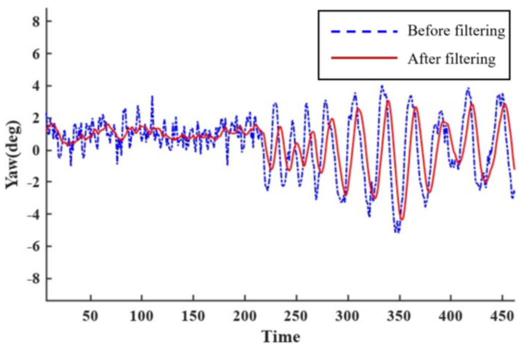

Figure 7. Data before and after yaw angle filtering

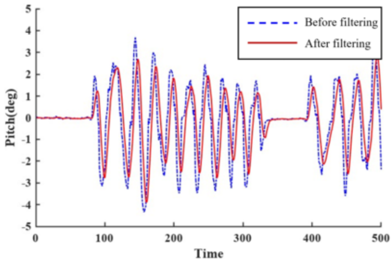

Figure 8. Data before and after pitch angle filtering

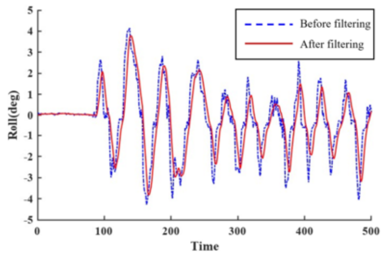

Figure 9. Data before and after roll angle filtering

5. Conclusion and foresight

This paper presents a human motion capture system based on inertial sensors. By installing inertial nodes on various joints of the human body, the system wirelessly transmits nine-axis data to the host computer in real-time. The system calculates and displays real-time attitude angle data through attitude calculation, and enhances data stability using a two-stage extended Kalman filter algorithm. The system is cost-effective, easy to wear, and does not interfere with normal human movement.

The disadvantage of this system is that there is no error correction for the initial data of the sensor, resulting in a certain deviation of the motion data. In the filtering algorithm experiment, there is no experiment of other algorithms such as complementary filtering, and the filtering result is relatively single. In the future, further processing and analysis of sensor data will be added to optimize the effectiveness of the algorithm.

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