RESEARCH ARTICLE

Enhanced Recognition for Finger Gesture-Based Control in Humanoid Robots Using Inertial Sensors

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Abstract

Humanoid robots have much weight in many fields. Their efficient and intuitive control input is critically important and, in many cases, requires remote operation. In this paper, we investigate the potential advantages of inertial sensors as a key element of command signal generation for humanoid robot control systems. The goal is to use inertial sensors to detect precisely when the user is moving which enables precise control commands. The finger gestures are initially captured as signals coming from the inertial sensor. Movement commands are extracted from these signals using filtering and recognition. These commands are subsequently translated into robot movements according to the attitude angle of the inertial sensor. The accuracy and effectiveness of the finger movements using this method are experimentally demonstrated. The implementation of inertial sensors for gesture recognition simplifies the process of sending control inputs, paving the way for more user-friendly and efficient interfaces in humanoid robot operations. This approach not only enhances the precision of control commands but also significantly improves the practicality of deploying humanoid robots in real-world scenarios.

Keywords: inertial sensor, finger gesture, NAO humanoid robot, quaternions, motion capture.

1 Introduction

Gesture recognition is an essential part of Human-Computer Interaction (HCI), and it has become a prominent area of study interest in recent years [1]. The two primary categories of gesture recognition methods available today are inertial sensor-based and visual capture-based [2].

Cameras are used in vision-based gesture recognition to capture images or videos, followed by computationally intensive image processing and computer vision algorithms to interpret these gestures. Gesture recognition technology can be utilized to monitor finger movements, thereby enhancing the security and convenience of biometric authentication systems commonly found in smartphones [3]. This approach fails when the line of sight is obstructed, and RGB cameras can be very limited in their use due to the large amount of hardware resources required to handle demanding computational tasks [4–6].

In contrast, inertial sensor-based gesture recognition offers several advantages. A significant advantage of this technique is that it is less sensitive to

Academic Editor:
Sushil Kumar Singh

Submitted: 11 September 2024
Accepted: 15 October 2024
Published: 30 October 2024

Vol. 1, **No.** 2, 2024.
10.62762/TSCC.2024.805710

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Citation
Xie, J., Na, X., & Yi, S. (2024). Enhanced Recognition for Finger Gesture-Based Control in Humanoid Robots Using Inertial Sensors. *IECE Transactions on Sensing, Communication, and Control*, 1(2), 89–100.

environmental variables, including various light conditions. This means that the inertial sensor-based gesture recognition system maintains good performance and accuracy both in bright sunlight and in dimly lit rooms [7, 8]. By measuring changes in acceleration and angular velocity, inertial sensors can accurately identify finger gestures [9, 10]. This approach has been widely used in a variety of scenarios, an example of which is handwritten character recognition using a handheld pen. In this application, inertial sensors are able to accurately capture the movement trajectory of the pen tip, enabling real-time recognition and translation of the written content [11]. In addition, the technology is also used for TV operation via handheld controllers [12], enabling users to control channels, volume and other functions through simple gestures, which greatly enhances the user experience. In addition to this, researchers are also exploring another innovative application of inertial sensors on the forearm to recognize gestures in active video games. These algorithms have been developed to provide gamers with a new way of interacting with each other, allowing them to control the game through natural hand movements, which in turn replaces traditional input devices such as mice or gamepads [13]. Therefore, gesture recognition tasks based on inertial sensors have very promising applications [14–16].

Recent studies have further advanced the capabilities of inertial sensor-based gesture recognition [17, 18]. Using wearable sensors, Dong et al. [19] created a deep learning framework for dynamic hand gesture identification, demonstrating improved accuracy and robustness. Lee et al. [20] introduced a method combining inertial sensors with machine learning algorithms to enhance the real-time detection and classification of complex hand gestures. Additionally, the integration of inertial sensors with other sensory inputs has been explored to provide multimodal gesture recognition systems, as discussed in Theodoridou et al. [21]. Provides a more reliable and accurate gesture recognition system through multi-sensor information fusion technology [22]. At the same time, sensor-based activity recognition technology using deep learning methods has also been applied to health monitoring for chronic disease patients and gesture recognition in gaming consoles [23]. These systems leverage the complementary strengths of different sensors to achieve more reliable and precise gesture recognition.

Similar to applications demonstrated in previous studies, this research investigates the use of inertial sensors to recognize changes in finger gestures and transmit commands wirelessly to a robot. In order to achieve reliable finger gesture identification, algorithms with higher precision and faster processing speed must be developed, given the smaller angles involved in finger movements. Only four differential equations must be solved in this study in order to compute the attitude matrix and determine the attitude angle thanks to the use of quaternions. This approach not only reduces computational load but also circumvents the issue of 'singularity,' thereby enhancing calculation efficiency.

The potential applications for robust and efficient gesture recognition systems are vast [24, 25]. From improving user interfaces in consumer electronics to enabling more intuitive control of robotic systems, the advancements in this field can significantly enhance the usability and adaptability of various technologies.

The following sections comprise the substance of this paper: Section 2 introduces how to calculate the attitude matrix and reduce the noise by the online smoothing filter. Section 3 gives the definition of gestures and discusses how to recognize gestures by inertial sensor, and the threshold selection. Experiments demonstrating the functionality of the developed system are given in Section 4, along with a demonstration of the robot's locomotion. The conclusion is presented in Section 5 along with recommendations for further investigation.

2 The calculation of attitude matrix

Determining the attitude angle is the primary function of a wearable multi-sensor system. Processing the attitude matrix is necessary to get the precise attitude angle. One method of calculating attitude angle is Euler algorithm, by which each differential equation contains many trigonometric functions. Furthermore, the equation has a "singularity" problem and the computing speed is slow. Another method is direction cosine method, in which nine differential equations need to be calculated and it will lead to large amount of calculation and poor real-time performance. Finally, quaternion method is represented by just four scalars. Consequently, the computation of trigonometric functions can be circumvented. In addition, compared to the Euler angle and direction cosine matrix, it has the benefit of having no singularity as the angle approaches ninety degrees and having a higher computing efficiency. Methods using Kalman filtering (KF) and untraceable Kalman filtering (UKF) can

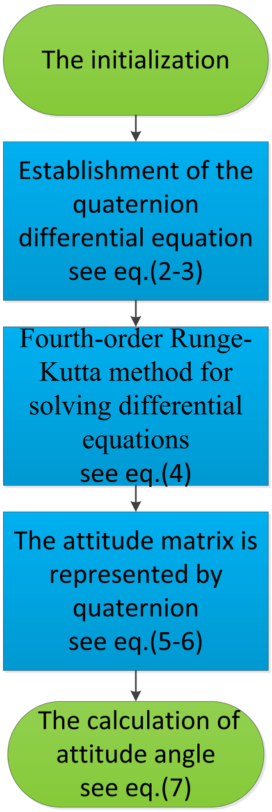


Figure 1. Flow diagram of quaternions method.

process sensor data and improve attitude estimation accuracy, but performance degrades in the face of nonlinearity [26, 27]. Therefore, based on the above advantages, this study decided to use quaternions for the calculation of attitude angle.

The method of calculating the attitude matrix by quaternion method is as follows [28]:

1) Initialization of quaternions (q_0, q_1, q_2, q_3)

$$q = \begin{bmatrix} q_0 & q_1 & q_2 & q_3 \end{bmatrix}^T, \quad q_0^2 + q_1^2 + q_2^2 + q_3^2 = 1 \tag{1}$$

2) The angular velocity values of each axis $\omega_x, \omega_y, \omega_z$ are measured by the inertial sensor and construct the equation (2) in order to get the updated value of quaternion.

$$\dot{q}(t) = \frac{1}{2} M(\omega) q(t) \tag{2}$$

$$M(\omega) = \begin{bmatrix} 0 & -\omega_x & -\omega_y & -\omega_z \\ \omega_x & 0 & \omega_z & -\omega_y \\ \omega_y & -\omega_z & 0 & \omega_x \\ \omega_z & \omega_y & -\omega_x & 0 \end{bmatrix} \tag{3}$$

where $\omega_x, \omega_y, \omega_z$ represent the measurements obtained from the gyroscope.

3) The differential equation (2) is solved using the Fourth-order Runge-Kutta method, with the specific formulation provided in equation (4).

$$\begin{cases} K_1 = \Gamma(t) q(t) \\ K_2 = \Gamma\left(t + \frac{h}{2}\right)\left(q(t) + \frac{h}{2} K_1\right) \\ K_3 = \Gamma\left(t + \frac{h}{2}\right)\left(q(t) + \frac{h}{2} K_2\right) \\ K_4 = \Gamma\left(t + \frac{h}{2}\right)\left(q(t) + h K_3\right) \\ q(t+h) = q(t) + \frac{h}{6}\left(K_1 + 2K_2 + 3K_3 + K_4\right) \end{cases} \tag{4}$$

where K represents slope, t is the present moment, h represents the update step, $\Gamma_b = \frac{1}{2} M(\omega)$, $M(\omega)$ is the matrix expression of three-axis angular velocity.

4) After using the Runge-Kutta method to solve the differential equation and obtain $q(t)$, attitude matrix C can be expressed in the form of quaternion, as shown in equation (5).

$$C = \begin{bmatrix} q_0^2 + q_1^2 - q_2^2 - q_3^2 & 2(q_1 q_2 - q_0 q_3) & 2(q_1 q_3 + q_0 q_2) \\ 2(q_1 q_2 + q_0 q_3) & q_0^2 - q_1^2 + q_2^2 - q_3^2 & 2(q_2 q_3 - q_0 q_1) \\ 2(q_1 q_3 - q_0 q_2) & 2(q_2 q_3 + q_0 q_1) & q_0^2 - q_1^2 - q_2^2 + q_3^2 \end{bmatrix} \tag{5}$$

To express simply, we rewrite attitude matrix C as equation (6)

$$C = \begin{bmatrix} C_{11} & C_{12} & C_{13} \\ C_{21} & C_{22} & C_{23} \\ C_{31} & C_{32} & C_{33} \end{bmatrix} \tag{6}$$

And then the attitude angle is calculated by the method of inverse trigonometric function, as shown in equation (7). Flow diagram of algorithm is shown in Figure 1.

$$\begin{cases} \theta = \arcsin(-C_{31}) \\ \gamma = \arctan \frac{C_{32}}{C_{33}} \\ \psi = \arctan \frac{C_{21}}{C_{11}} \end{cases} \tag{7}$$

where ψ, θ, γ denotes yaw, pitch, and roll; specifically, pitch represents the rotational angle about the X-axis (illustrated in Figure 2(a)), roll corresponds to the rotational angle about the Y-axis (illustrated in Figure 2(b)), and yaw refers to the rotational angle about the Z-axis (illustrated in Figure 2(c)) [29].

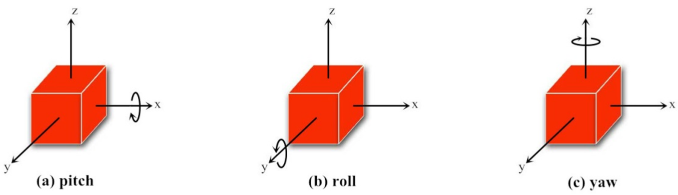


Figure 2. The sketch map of pitch, yaw and roll.

Figure 3. The finger attached to the inertial transducer.

3 The gesture processing based on the inertial sensor

3.1 The gesture processing based on the inertial sensor

Robot movement in complex environments plays a crucial role, so we introduced a remote control system [30]. Remote control system here includes a Nao humanoid robot, an inertial sensor and the computer, shown in Figure 3. The Nao is manufactured by Aldebaran Robotics. The company opens the Nao technology to all higher education projects and Nao can be visualized by the ready instruction module. The design of hardware uses the latest manufacture technology in order to ensure the smooth operation of Nao. In addition, Nao is equipped with a variety of advanced sensors, which enable it to perceive the surrounding environment more accurately, significantly enhancing the robot's interactive capabilities and the flexibility of its autonomous decision-making [31]. As a classical robot experiment platform, Nao humanoid robot has the function to keep itself stable when walking, and each action of the robot has a corresponding program code. To enable movement of the robotic arm, the corresponding program code must be transmitted to it via a computer [32].

Here the movement of the finger is detected and through the inertial sensor to send the motion commands to control the robot. The inertial sensor is produced by the Beijing iGyro Technology Co., Ltd and it contains the gyroscope, the accelerometer and the magnetometer [33]. The inertial sensor can detect the acceleration, position and attitude of target. In order to detect finger gestures during the experiment, the inertial sensor is fastened to the user's finger. In Figure 4, the algorithm is illustrated.

The signal of inertial sensor is caught when the finger moves. Subsequently, a smoothing filter is employed to process the motion signal [34]. By the quaternion method the filtered signal is used to obtain the attitude angle. Then based on the angles, i.e., yaw, pitch and roll, the command about moving mode is calculated, seeing details in Section 3.2 and 3.3.

Firstly, we describe the filtering process: we employ a smoothing filter to denoise the gyroscope measurements, using a smoothing window size of 50. Next, we consider the relationship between the user's gestures and the robot's walking commands, and we design the control strategy for the Nao robot based on inertial sensor data as follows:

1. when the user's finger is lifted from a horizontal position, the robot moves forward;
2. when the user's finger is turned downward, the robot stops;
3. when the user directs their finger to the right, the robot rotates to the right;
4. when the user directs their finger to the left, the robot rotates to the left.

The finger gestures and corresponding robot movements are illustrated in Figure 5. Subsequently, sections 3.2 and 3.3 will be addressed, we will discuss the methods to accurately extract the correct gesture based on inertial sensor signals. In Section 3.2, we will examine the features of different gestures and, to avoid command errors, how the appropriate threshold values are selected in Section 3.3.

3.2 Gesture recognition

The key of the system developed here is to recognize the finger gestures. The first step of gesture recognition is to determine the starting point of movement, which will set down the initialization of quaternions and keep the different equation (2) of quaternion have the right solution. When the original value of angular velocity reaches a certain degree, the gesture is recognized. This approach effectively eliminates interference from the inertial sensors. As to the signal of inertial sensor fixed on the finger, when the finger moves, three signal, called X, Y, Z axis will be obtained. The inertial sensor can record the change of angular velocity of the finger

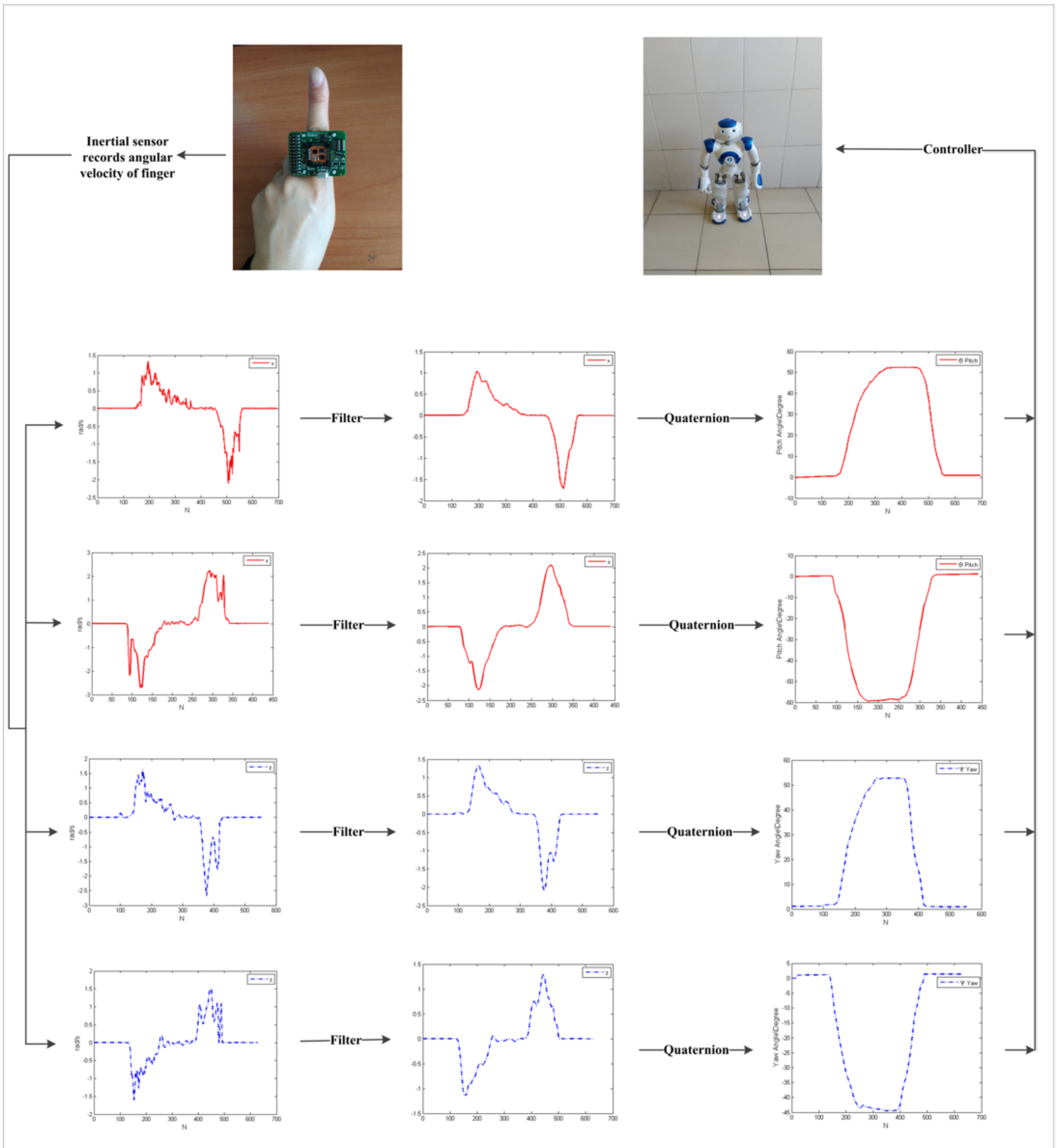


Figure 4. The diagram of the algorithm.

moving so that the finger gesture can be determined (the details are shown in Figure 6).

When the finger is up or down, the angular velocity of the X axis will change. Upward or downward gestures can be judged by the sequence of peak and valley. Similarly, when the finger turns right or left, the angular velocity of the Z axis will change. Gestures to the left or right can also be judged by the sequence of peak and valley. The relationship between the positive and negative changes of angular velocity and finger gesture, as shown in Table 1. The '+' represents the angular velocity is positive, '-' on behalf of angular velocity is negative, '####' represents no change in angular velocity. Here the signal of the y-axis is omitted, because as to the movement mode we considered, it will change very little.

Table 1. The relation between angular speed signals and gestures.

	X axis	Z axis
Finger Up	+-	####
Finger Down	-+	####
Finger Right	####	+-
Finger Left	####	-+

But we don't want to detect the gestures based on the angular velocity x and z directly. Because it's difficult to detect the sequence of peak and valley with high correct rate. Next, we use the quaternion method to obtain the attitude angles, as shown in Figure 7.

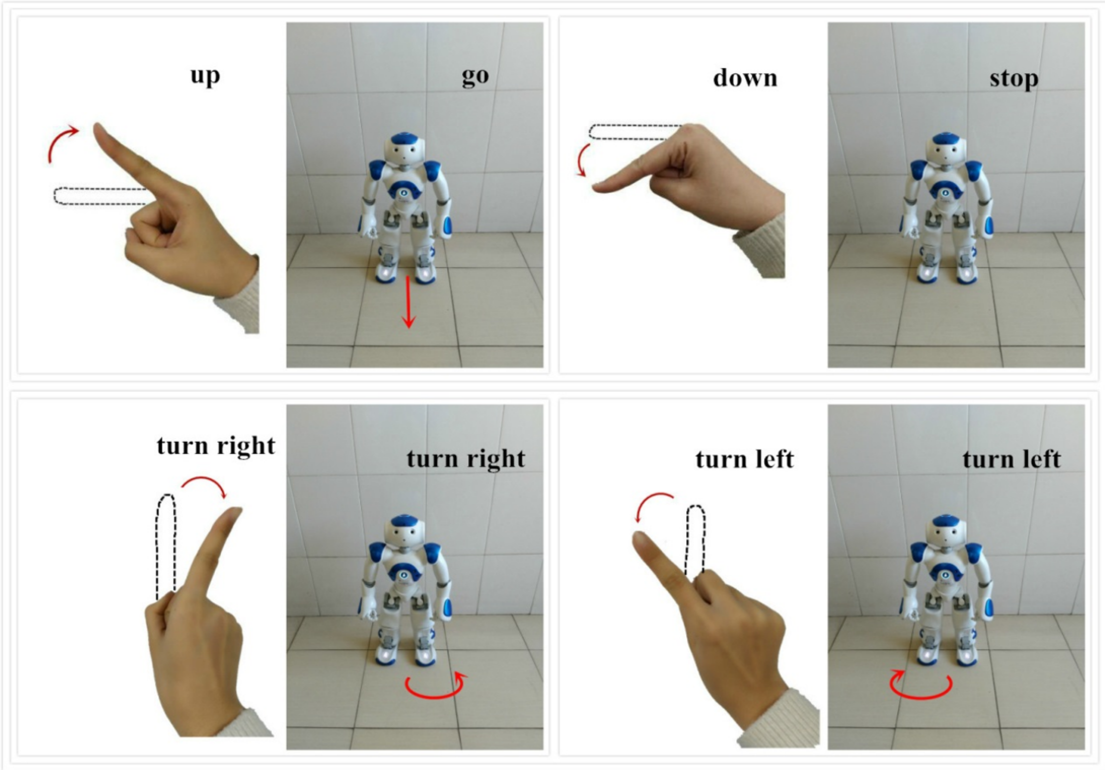


Figure 5. The relation of gesture and robot movement.

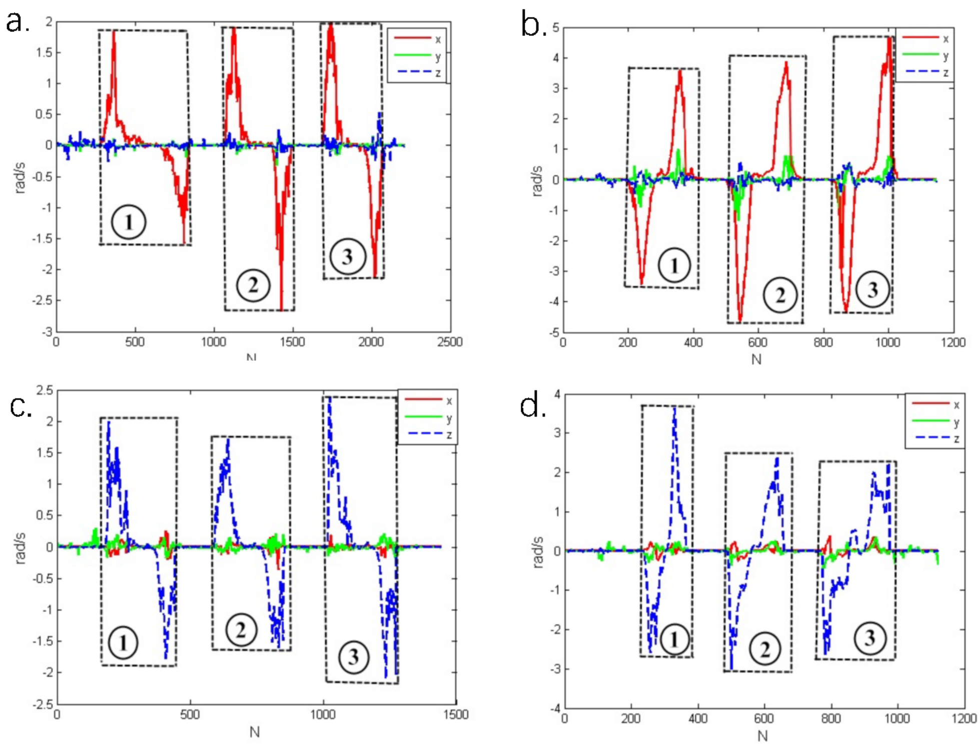
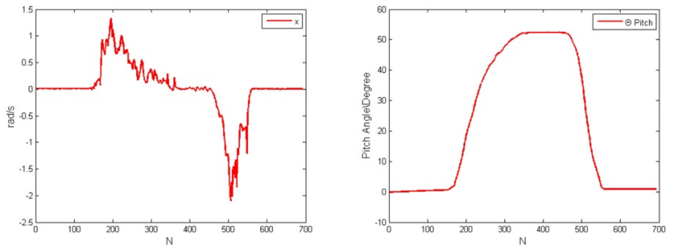
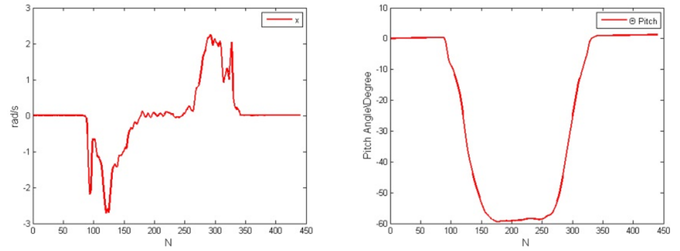


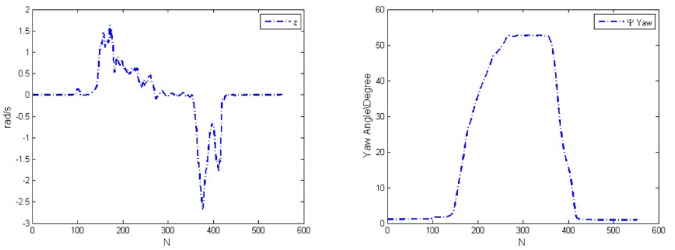
Figure 6. The angular velocity of the X axis when the finger is moving. **a**. When the finger is lifted, the angular velocity of X axis is positive. When the finger comes back to its original position, the angular velocity is negative. This process reflects a peak and a valley in the X axis and the peak is in front of the valley. **b**. When the finger is downward from the horizontal position, the angular velocity of X axis is negative, then positive. **c**. When the user's finger turns right, the angular velocity of Z axis will change, and is positive. **d**. When the user's finger turns left, the angular velocity of Z is negative. When the finger comes back to its original position, the angular velocity is positive. This process reflects a valley and a peak in the Z axis and the valley is in front of the peak.



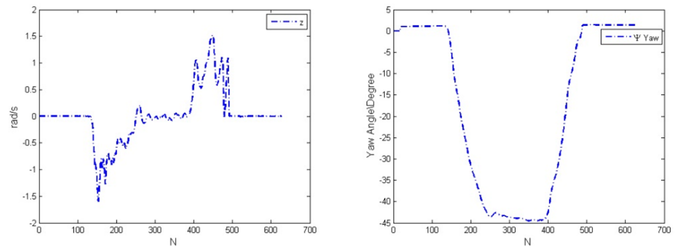
(a) The measurement of angular velocity and attitude angle when the finger is lifted.



(b) The measurement of angular velocity and attitude angle when the finger is turned down.



(c) The measurement of angular velocity and attitude angle when the finger turns right.



(d) The measurement of angular velocity and attitude angle when the finger turns left.

Figure 7. The relation of gestures and the attitude angles.

Figures 7(a) and 7(b) illustrate the relationship between X-axis angular speed and pitch angle, with Figure 7(a) depicting a positive pitch and Figure 7(b) illustrating a negative pitch. Figures 7(c) and 7(d) demonstrate the relationship between Z-axis angular speed and yaw angle, where Figure 7(c) presents a positive yaw and Figure 7(d) presents a negative yaw. The sequence of peaks and valleys is altered, resulting in distinct peaks or valleys corresponding to varying pitch and yaw angles. Then in the next section, we will discuss how to obtain the control command based the obtained attitude angle.

3.3 The threshold analysis

In this system, the motion of the Nao robot is controlled through finger gestures, which encompass raising, lowering, turning right, and turning left. These movements are defined as $Figure\_Up$, $Figure\_Down$, $Figure\_Right$ and $Figure\_Left$ respectively.

Because the inertial sensor is fixed on the finger, the slight movements of user's finger result in the inaccuracy of gesture recognition. Therefore, a minimum angle is established to minimize the impact of noise. To determine a reliable minimum angle, offline experiments are conducted for analysis, and the recorded angular data are presented in Figure 8. In the experiments, we discover that the pitch range between -20 and 20 degrees may be brought on by a tiny finger jitter, which could result in an incorrect command. Thus, we established a minimum pitch angle of $\pm$20 degrees, as shown by the green line in Figure 8.

Conversely, if the user raises their finger without paying attention to steer the robot's movement, the inertial sensor will measure the data with a large attitude angle. In order to avoid such a situation, a maximum angle is established to prevent the robot from executing incorrect movements. Similar to the minimum angle, several experiments are carried out to find a reasonable maximum angle. Finally, the maximum angle T_2 is set as $\pm$50 degrees to avoid the wrong command when the finger is lifted, which is seen in Figure 8 by the yellow line. In the event that the angle is sufficiently greater than the maximum value, the robot will also stay still. Therefore, a threshold value can be established between $\pm$20 and $\pm$50 degrees to accurately represent the pitch angle.

When the finger rotates to the right, the angle of the thumb will be expressed as a positive degree; conversely, When the finger rotates to the left, the angle will be represented as a negative degree. Similar to the pitch, we select the threshold T_3 as $\pm$20 degrees and T_4 as $\pm$40 degrees to accurately reflect the angle of yaw. In the Figure 9, the green lines indicate T_3 and the yellow lines indicate T_4. The rules to detect the movement of finger are as shown in the equations (8) (9).

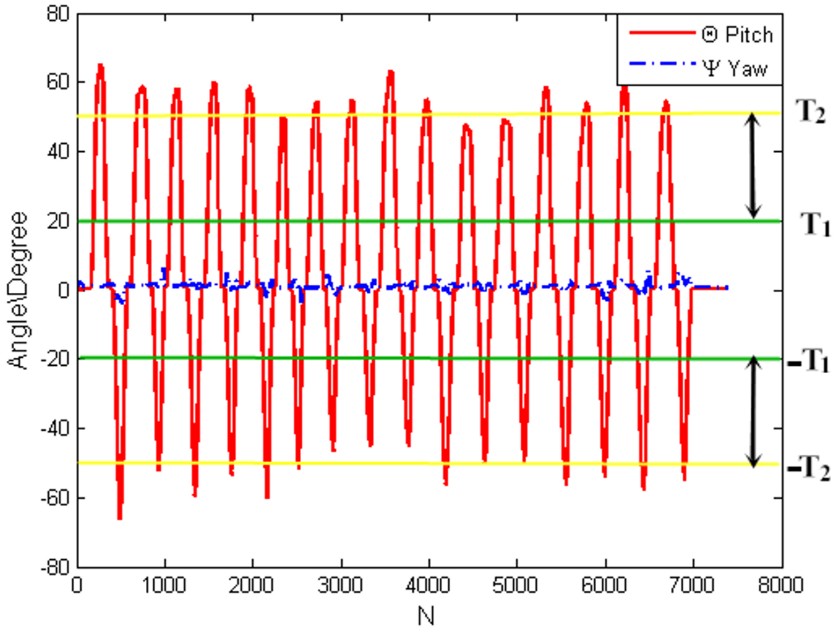


Figure 8. The range of pitch angle.

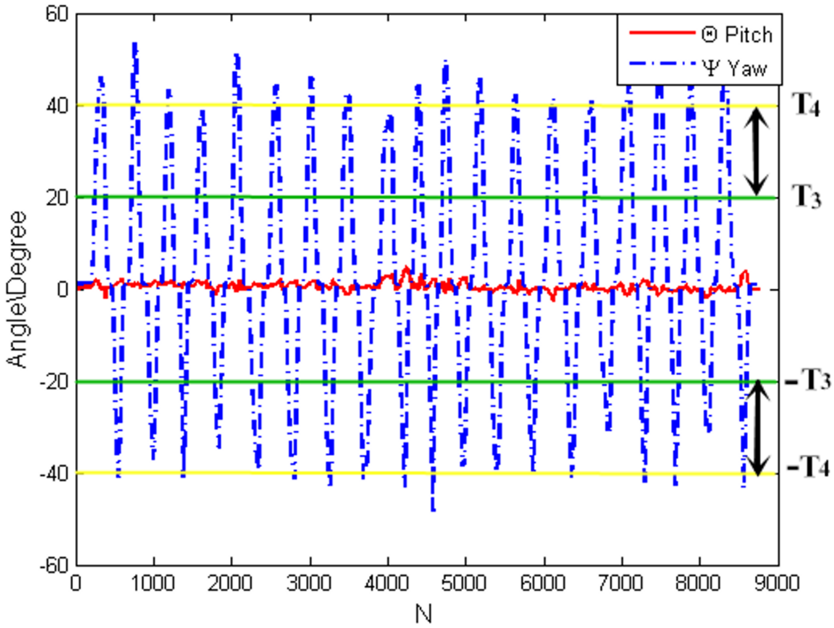


Figure 9. The range of yaw angle.

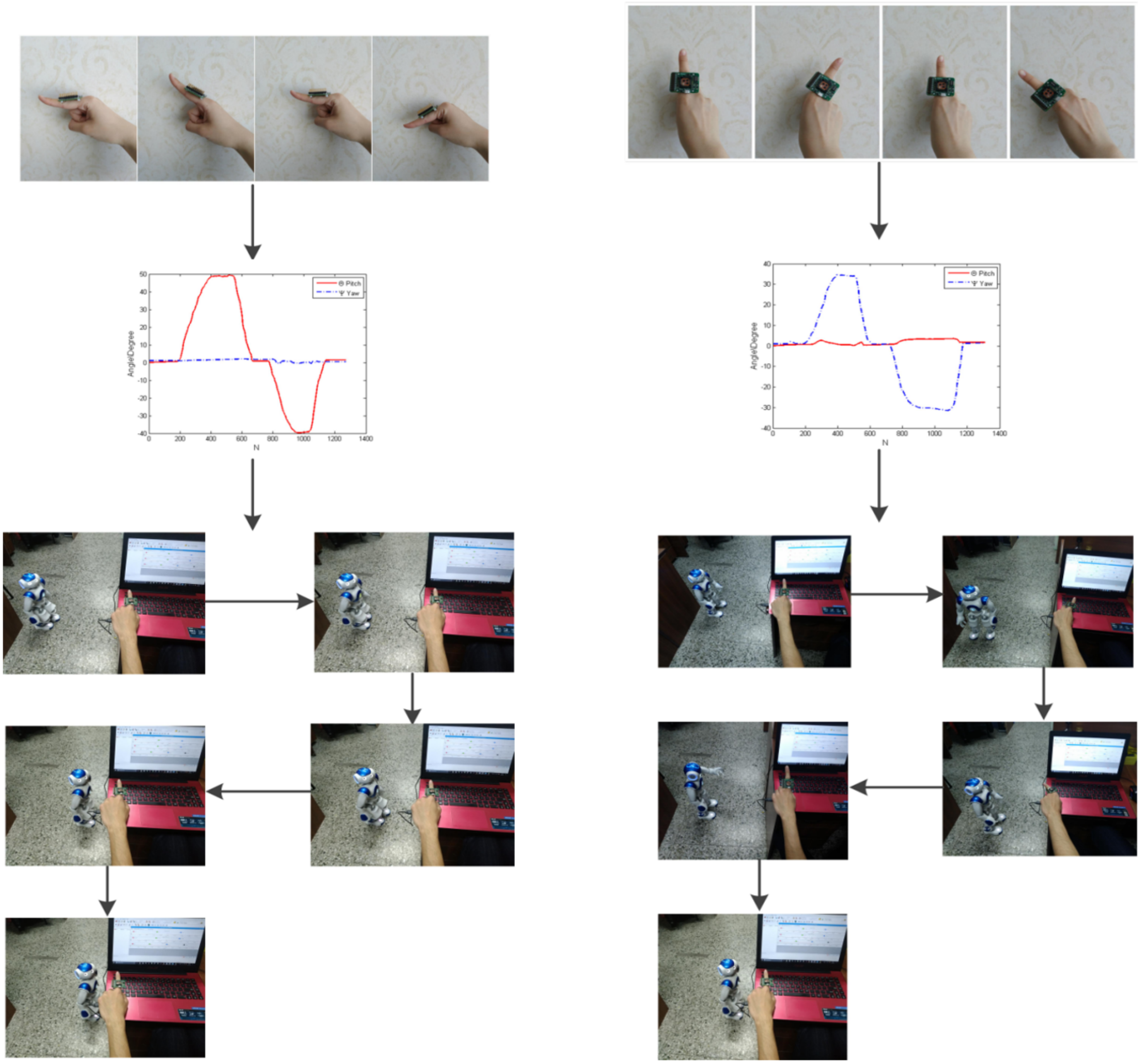
$$\begin{cases} T_1 < \text{Pitch} < T_2 \implies \text{Finger\_Up} \\ -T_2 < \text{Pitch} < -T_1 \implies \text{Finger\_Down} \end{cases} \tag{8}$$

$$\begin{cases} T_3 < \text{Yaw} < T_4 \implies \text{Finger\_Right} \\ -T_4 < \text{Yaw} < -T_3 \implies \text{Finger\_Left} \end{cases} \tag{9}$$

We note that pitch belonging to $[T_1, T_2]$ means that the finger is lifted up, pitch belonging to $[T_1, T_2]$ means that the finger is down, yaw belonging to $[T_3, T_4]$ means that the finger is turned right, and yaw belonging to $[-T_4, -T_3]$ means that the finger is turned left.

4 Control for NAO robot

As a classic robot platform, the Nao robot has a comprehensive self-action module. Upon receiving movement commands, Nao can walk while maintaining self-balance. Therefore, our primary focus is on whether Nao can accurately receive commands based on finger gestures. The computer obtains signals from the inertial sensor, interprets the finger gestures, and then sends the corresponding movement commands to the Nao robot. In this study, four commands are described by character instructions: ‘G’, ‘S’, ‘R’, and ‘L’, with their



(a) Control the robot to go forward and stop.

(b) Instruct the robot to rotate to the right and left.

Figure 10. The finger gestures and robot movements.

Table 2. Definition of commands.

Command	Definition
G	controlling the robot to go forward
S	controlling the robot to stop
R	controlling the robot to turn right
L	controlling the robot to turn left

definitions listed in Table 2.

When the finger is lifted upwards, the inertial sensor detects a positive pitch angle, prompting the robot to receive the corresponding instruction 'G', which triggers forward movement. Conversely, when the finger is turned downwards, the sensor detects a negative pitch angle, resulting in the robot receiving the 'S' instruction to stop. For lateral movements, when the finger is turned right, the inertial sensor detects a positive yaw angle, leading to the robot receiving the 'R' instruction to turn right. Similarly, when the finger is turned left, a negative yaw angle is detected, prompting the 'L' instruction for the robot to turn left.

As illustrated in Figure 10, the inertial sensor detects changes in the finger's angular velocity when it is lifted, lowered, or turned left or right. The quaternion method is then employed to convert this angular velocity into an attitude angle. The robot receives this angle signal and executes the corresponding action based on the command.

Figure 10(a) demonstrates that when the finger is lifted, a positive pitch angle is registered, directing the robot to move forward. When the finger is lowered, a negative pitch angle is detected, commanding the robot to stop. Figure 10(b) shows that when the finger is turned right, a positive yaw angle is recorded, instructing the robot to turn right. Conversely, when the finger is turned left, a negative yaw angle is detected, prompting the robot to turn left.

5 Conclusion

This paper presents a new method for robot remote control using gesture detection from inertial sensors. The principle idea is to use inertial sensors to track the movements and direction of fingers and send corresponding commands to the robot through wireless communication. This approach intends to deliver an approachable and responsive control mechanism. Our method computes the attitude matrix using quaternions to obtain the attitude angles of finger movement with high accuracy and reliability. Quaternions are very useful because they reduce the computation complexity and we solve only 4 differential equations. Moreover, quaternions provide efficient resolution to the problem of 'singularity,' which is common with classical methods, enhancing the overall performance and robustness of the system. The results show that our proposed method is effective and robust in many environments and lighting conditions, and that inertial sensor-based gesture recognition can greatly outperform vision-based methods. The potential for improving accuracy and real-time performance, along with providing adaptability for different user gestures and commands is demonstrated with a proposed system.

Future work will include extending the scope of detectable gestures and improving the system's adaptability to complicated and intricate finger movements. Furthermore, because the proposed method can be embedded in the pipeline for other sensory units, employing it alongside advanced machine learning methods can enhance its accuracy and generalization, making it useful for various human-computer interaction and robotics applications. In conclusion, the proposed method marks a major advancement toward developing intuitive, accurate, and fast gesture-controlled robots using the advantages of inertial sensor technology to overcome the disadvantages of traditional vision-based approaches.

Conflicts of Interest

The authors declare no conflicts of interest.

Funding

This work was supported without any funding.

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