RESEARCH ARTICLE

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

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Abstract

Humanoid robots play a significant role in numerous fields, where efficient and intuitive control inputs are essential, particularly in applications requiring remote operation. In this paper, we investigate the potential advantages of inertial sensors as a key component for generating command signals in humanoid robot control systems. The objective is to accurately detect user motion through inertial sensing, thereby enabling precise control commands. Finger gestures are first captured as signals from the inertial sensor, and movement commands are extracted through filtering and recognition processes. These commands are then translated into corresponding robot actions based on the sensor's attitude angles. Experimental results demonstrate the accuracy and effectiveness of this method in recognizing finger movements and converting them into reliable robot operations. The use of inertial sensors for gesture recognition simplifies the transmission of control inputs, promoting more user-friendly and efficient interfaces for humanoid robot operation. This approach not only improves control precision but also enhances the practicality of deploying humanoid robots in real-world environments.

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 research 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 efficiently recognize hand movements from IMU sensor data, enabling real-time learning and classification for a wide range of human-machine interface applications [3]. This approach fails when the line of sight is obstructed or when lighting conditions change, and RGB cameras impose severe constraints on hardware resources and computational cost, limiting their practical applicability across diverse environments [4–6].

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In contrast, inertial sensor-based gesture recognition offers several advantages. A significant advantage of this technique is that it is less sensitive to 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]. By measuring acceleration and orientation changes, inertial sensors can be used to accurately estimate position and attitude across a wide range of motion scenarios [11]. In addition, the technology is also applied to wireless control of mobile robots via body-worn inertial sensors [12], enabling users to issue movement commands through hand gestures and operate robotic platforms at distances of up to 250 m, which greatly expands the practicality of human-robot interaction. In addition to this, researchers are also exploring the application of wrist-mounted inertial sensors for recognizing arm gestures to control mobile robots in outdoor environments. These methods have been developed to enable operators to maneuver robotic platforms intuitively through natural arm movements, without relying on any static equipment such as joysticks [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, including real-time IoT-oriented gesture control systems for human-robot collaboration in industrial environments [17] and systematic surveys of wearable sensing interfaces and recognition algorithms covering classification and regression approaches for diverse gesture interaction tasks [18]. Using wearable MEMS inertial sensors, Wang et al. [19] investigated static and dynamic hand gesture recognition with preprocessing via low-pass filtering and normalization, demonstrating reliable recognition performance. Gromov et al. [20] demonstrated proximate human-robot interaction using pointing gestures detected by a wrist-mounted IMU, enabling intuitive and real-time robot control through natural hand movements. Additionally, inertial measurement units have been demonstrated as versatile sensing tools applicable across a wide range of application domains, including industry, medical rehabilitation, and human-machine interaction, owing to their compact size, low cost, and immunity to external lighting or occlusion [21]. Wearable inertial sensing systems using quaternion-based orientation tracking have demonstrated reliable motion measurement and evaluation across multiple body segments, establishing the technical basis for accurate gesture-based command generation in robotic control applications [22]. At the same time, gesture-based robot teleoperation has been further explored through optical sensor platforms, demonstrating that gesture recognition algorithms combined with signal smoothing can achieve stable and responsive wireless control of mobile robots [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

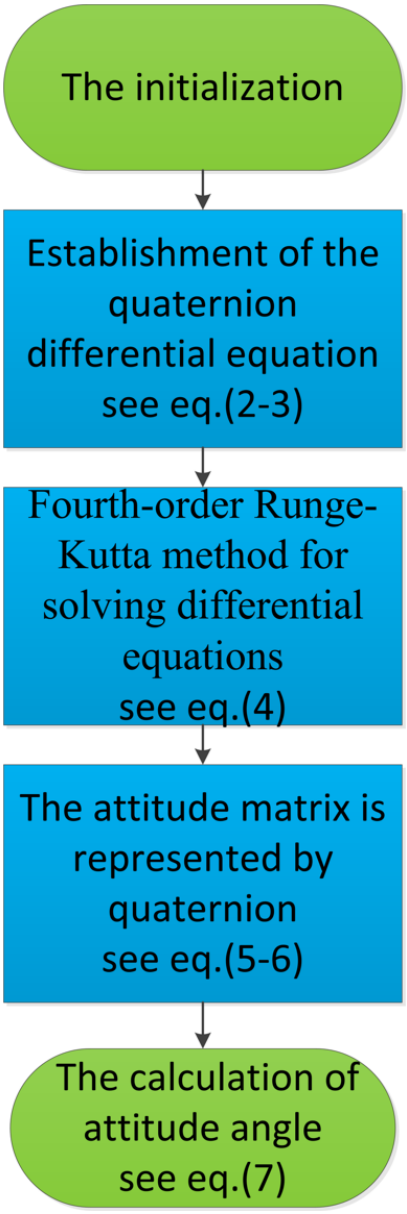


Figure 1. Flow diagram of quaternions method.

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 unscented Kalman filtering (UKF) can process sensor data and improve attitude estimation accuracy by fusing gyroscope, accelerometer, and magnetometer measurements via quaternion-based state representations [26, 27], but their performance may degrade under highly nonlinear or dynamic motion conditions. 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).

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

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

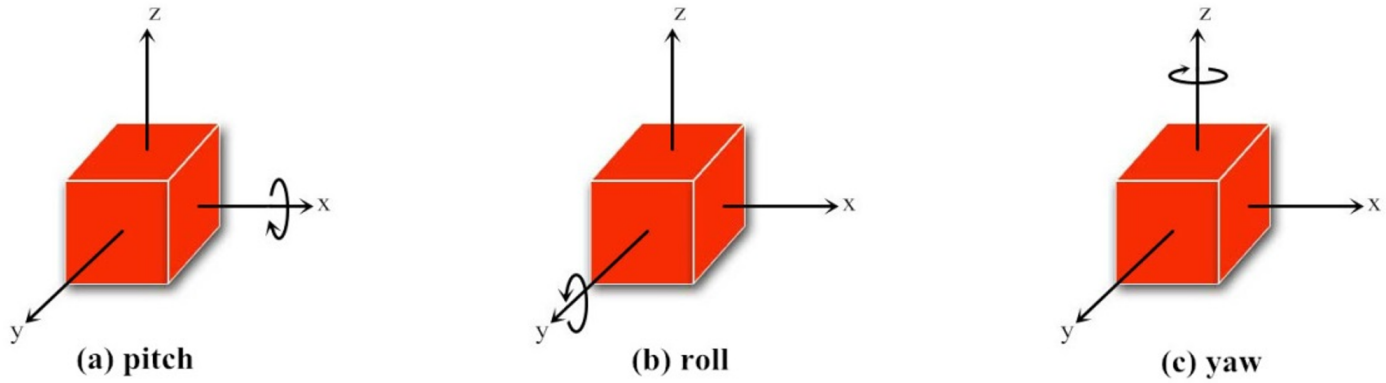


Figure 2. The sketch map of pitch, yaw and roll.

can be expressed in the form of quaternion, as shown in equation (5).

$$C = \begin{bmatrix} q_0^2+q_1^2-q_2^2-q_3^2 & 2(q_1q_2-q_0q_3) & 2(q_1q_3+q_0q_2) \\ 2(q_1q_2+q_0q_3) & q_0^2-q_1^2+q_2^2-q_3^2 & 2(q_2q_3-q_0q_1) \\ 2(q_1q_3-q_0q_2) & 2(q_2q_3+q_0q_1) & q_0^2-q_1^2-q_2^2+q_3^2 \end{bmatrix} \tag{5}$$

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.

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

where ψ, θ, γ denotes yaw, pitch, and roll; specifically, roll represents the rotational angle about the X-axis (illustrated in Figure 2(a)), pitch 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].

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 remote control of the robot, motion commands derived from wearable sensor data are transmitted wirelessly to the robot platform via a host computer, consistent with the teleoperation architecture established in earlier robotic systems [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. The inertial sensor can detect the acceleration, position and attitude of target, enabling wrist-worn and finger-mounted configurations to achieve real-time gesture recognition [33]. 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



Figure 3. The inertial sensor attached to the finger.

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

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

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 differential equation (2) of quaternion having 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 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.

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. 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 $Finger_Up$, $Finger_Down$,

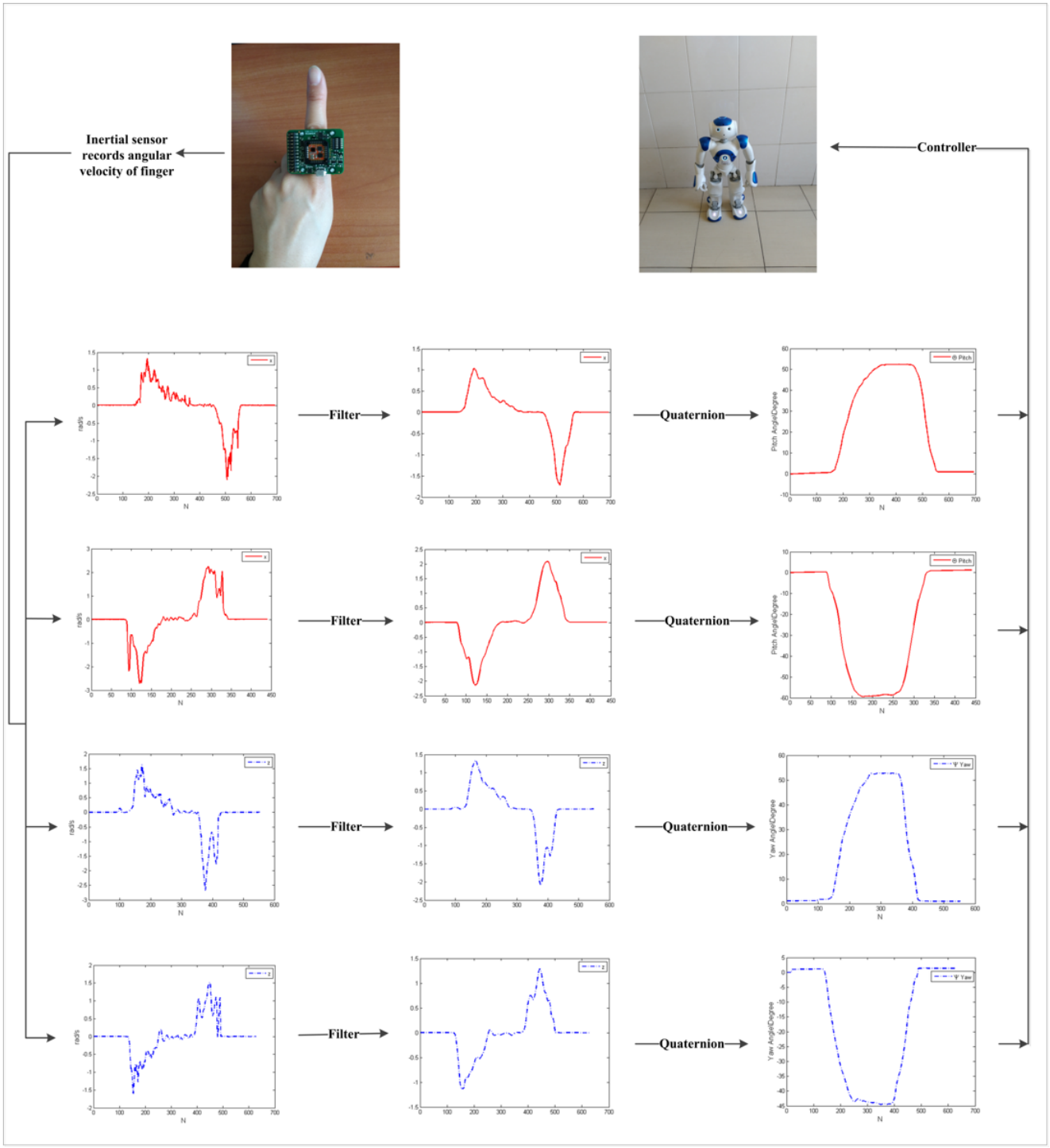


Figure 4. The diagram of the algorithm.

$Finger_Right$ and $Finger_Left$ 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

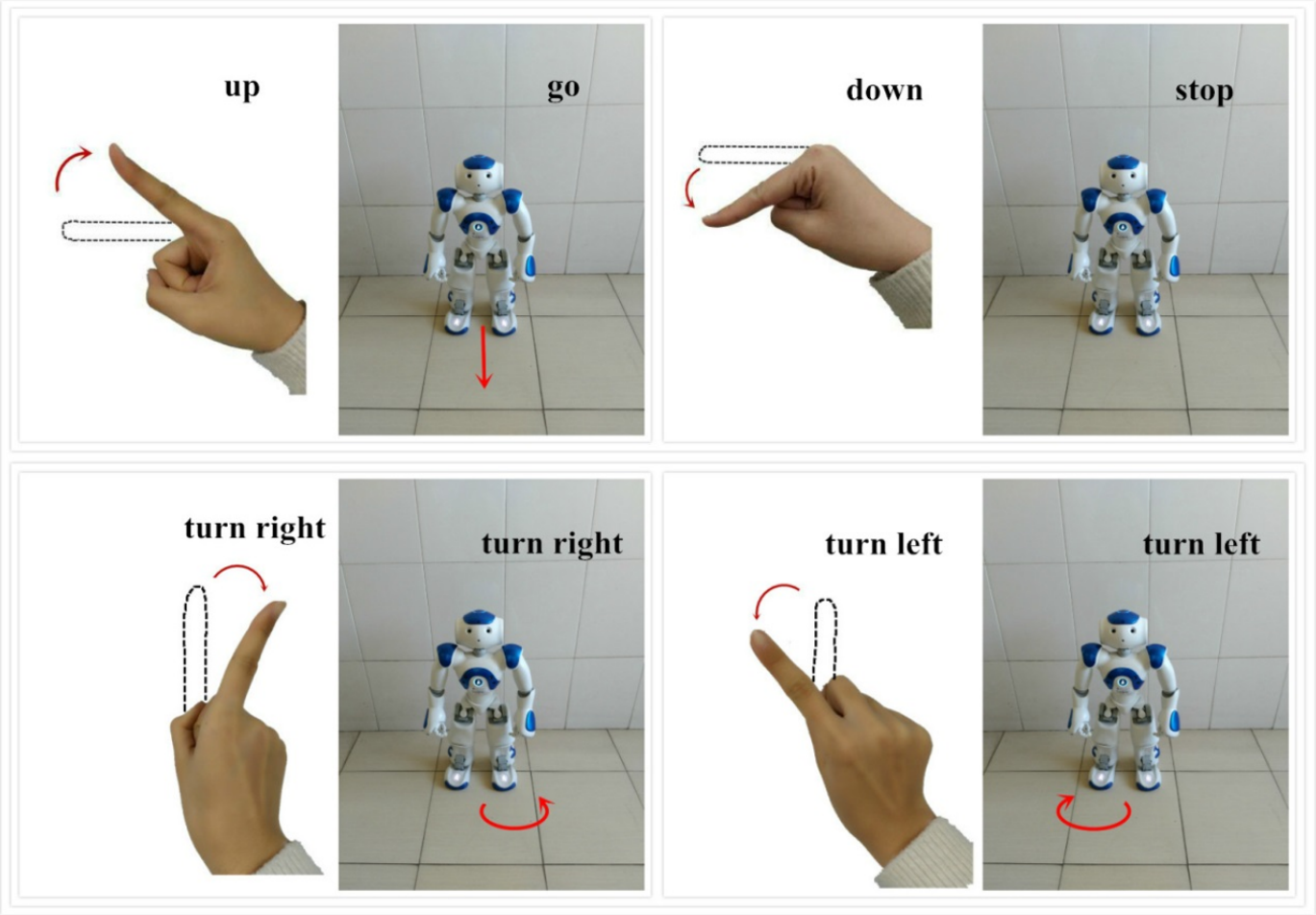


Figure 5. The relation of gesture and robot movement.

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 ± 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 ± 20 and ± 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 ± 20 degrees and T_4 as ± 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).

$$\begin{cases} T_1 < \text{Pitch} < T_2 \implies \text{Finger_Up} \\ -T_2 < \text{Pitch} < -T_1 \implies \text{Finger_Down} \end{cases} \tag{8}$$

$$\begin{cases} T_3 < \text{Yaw} < T_4 \implies \text{Finger_Right} \\ -T_4 < \text{Yaw} < -T_3 \implies \text{Finger_Left} \end{cases} \tag{9}$$

We note that pitch belonging to $[T_1, T_2]$ means that the finger is lifted up, pitch belonging to $[-T_2, -T_1]$ 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,

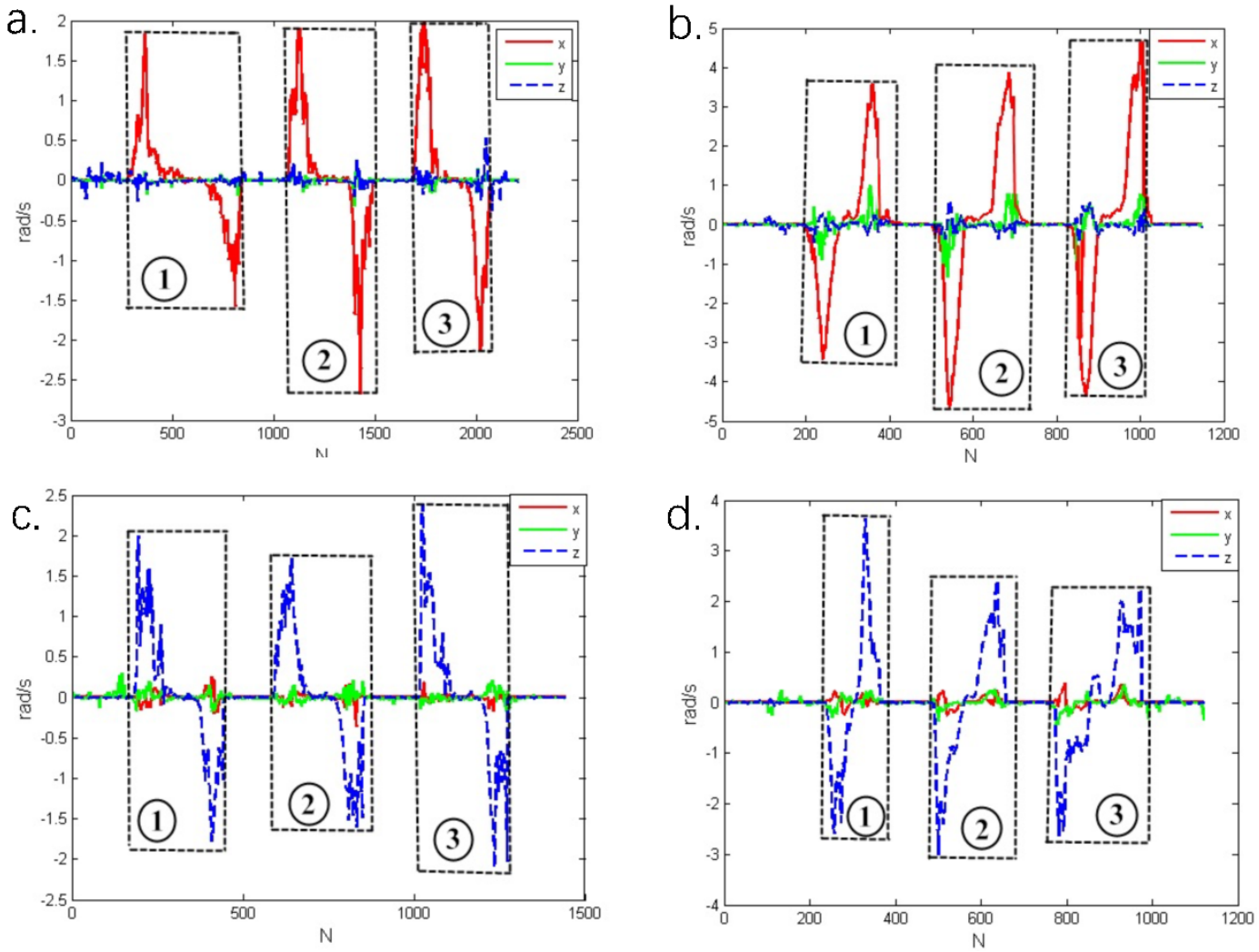


Figure 6. The angular velocity of the X axis when the finger is moving. **a**. When the finger is lifted, the angular velocity of X axis is positive. When the finger comes back to its original position, the angular velocity is negative. This process reflects a peak and a valley in the X axis and the 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.

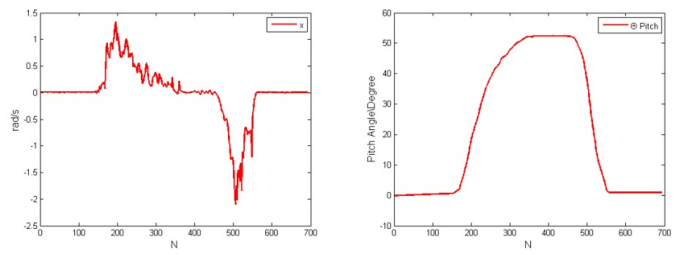
Table 2. Definition of commands.

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

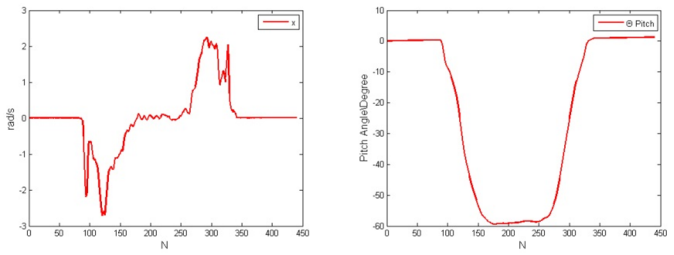
interprets the finger gestures, and then sends the corresponding movement commands to the Nao robot. In this study, four commands are described by character instructions: 'G', 'S', 'R', and 'L', with their definitions listed in Table 2.

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.

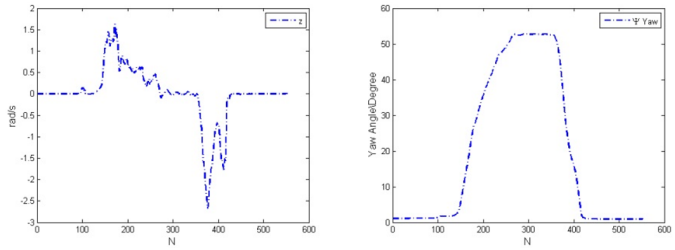
As illustrated in Figure 10, the inertial sensor detects changes in the finger's angular velocity when it is lifted, lowered, or turned left or right. The quaternion method is then employed to convert this angular



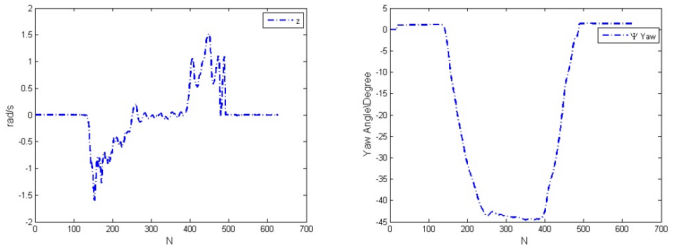
(a) The measurement of angular velocity and attitude angle when the finger is lifted.



(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.

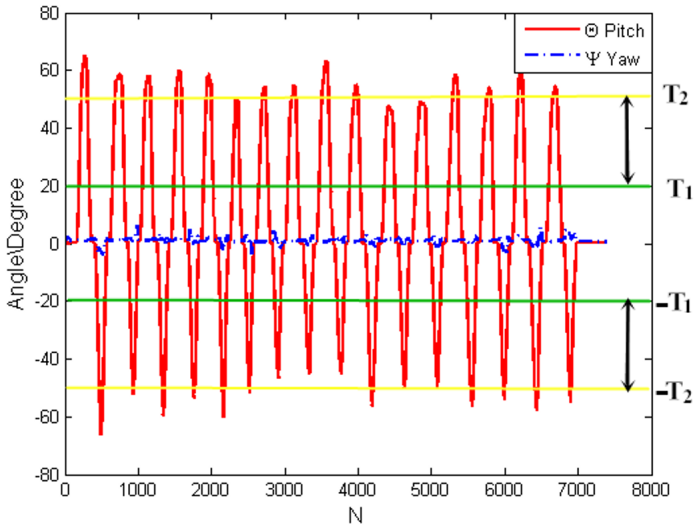


Figure 8. The range of pitch angle.

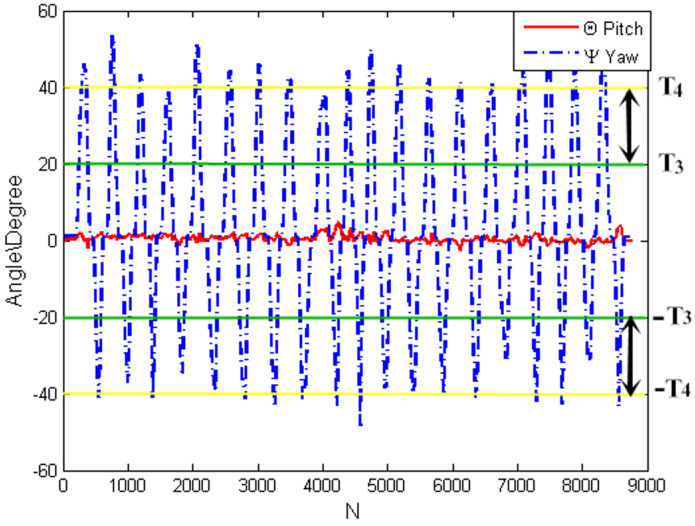


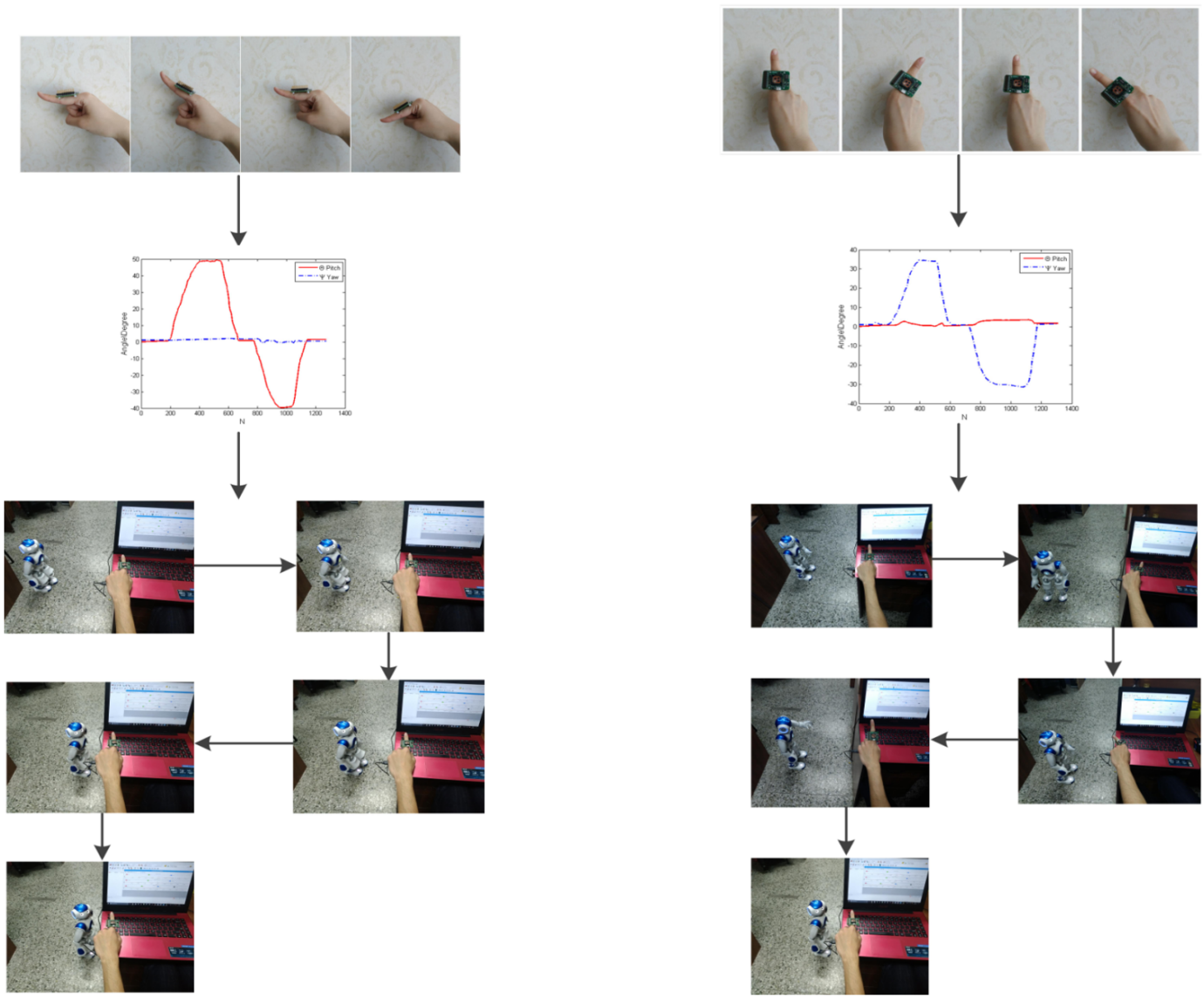
Figure 9. The range of yaw angle.

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



(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.

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.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

Shenglun Yi served as an Associate Editor of the *ICCK Transactions on Sensing, Communication, and Control* at the time of manuscript submission. To ensure the integrity of the peer-review process, Shenglun Yi was not involved in the editorial handling, peer review, or decision-making process for this manuscript, which was handled independently by another editor. The remaining authors declare no conflicts of interest.

Ethical Approval and Consent to Participate

Not applicable.

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