A Laser Lidar-Based Body Turning Detection Method in VR Interaction

Shufang Chen

Xian Peihua University, Xian, Shaanxi Province, 710125

Abstract: ***The traditional key-based operation modes of virtual reality (VR) interaction often suffer from insufficient immersion and limited hand operation, which hinder the natural and intuitive user experience. To address these challenges, this paper proposes a novel body turning detection method based on laser lidar technology. By aligning the laser lidar with the human back, the method systematically collects distance data in a 4×4 grid format. The collected data is then processed using mean value analysis to enhance accuracy and robustness. Based on the data relationships, the method effectively judges the turning direction and further calculates the body turning speed to control the platform speed in real-time. Experimental results demonstrate that this method can accurately and efficiently realize human body turning detection and speed regulation. By providing technical support for liberating hand operations, the method significantly enhances the realism and immersion of VR intelligent interaction. This innovative approach not only improves the user experience but also opens new avenues for the development of more advanced and user-friendly VR systems. The findings contribute to the broader field of human-computer interaction, offering practical insights for the design and optimization of VR technologies.***

Keywords: Laser lidar; Body turning detection; VR dynamic interaction; Turning speed calculation.

1. INTRODUCTION

Virtual reality (VR) technology is widely used in entertainment, education, healthcare, and other fields, with its core value lying in creating highly immersive virtual experiences for users. However, current VR motion platforms still exhibit clear limitations in interaction methods. Traditional key- or controller-based operations essentially extend the mouse-and-keyboard paradigm: users must use hand movements to simulate walking, turning, and other bodily motions. This “hands-for-body” interaction not only reduces the realism of the VR experience but also prevents the hands from performing other fine operations. As user expectations rise, interaction technologies based on natural body movements have become a research hotspot. Accurately detecting and perceiving actions such as walking, running, and turning, and then synchronizing virtual motion with real motion, is key to improving VR immersion. Among motion-detection technologies, LiDAR, with its high precision and non-contact measurement, offers a new solution for human-motion detection. This study focuses on the common action of body turning, exploring the use of LiDAR to detect back motion for efficient and accurate turn recognition, and further calculating body-turning speed to optimize VR platform control. The goal is to bring an innovative breakthrough to VR interaction technology, enhancing user experience and expanding VR application scenarios. Zheng, Zhou, and Lu (2023) developed an improved YOLOv5s algorithm for rebar cross-section detection [1], while Zhao, Zhang, and Hu (2023) applied a Res2Net-YOLACT+HSV model for smart warehouse track identification [2]. Further advancing the field, Shao, Wang, and Liu (2023) proposed a salient object detection algorithm leveraging diversity features and global guidance information [3]. Beyond traditional vision tasks, Ge and Wu (2023) conducted an empirical study on the adoption of ChatGPT for bug fixing among professional developers, highlighting the intersection of AI and software engineering [4]. The year 2025 witnessed a proliferation of novel frameworks across various sectors: Tu (2025) introduced ProtoMind for NAS and SIP message sequence modeling in smart regression detection [5]; Xie and Liu (2025) created InspectX to optimize industrial monitoring systems [6]; and Zhu (2025) developed REACTOR for reliability engineering with automated causal tracking [7]. Additional 2025 contributions include Zhang's (2025) AdOptimizer for efficient ad delivery [8], Hu's (2025) low-cost 3D authoring via guided diffusion [9], and Tan et al.'s (2024) highly reliable densely connected convolutional networks for fault diagnosis [10]. Research also extended to business applications with Zhuang (2025) exploring real estate marketing strategies under digital transformation [11], and Han and Dou (2025) proposing a user recommendation method integrating hierarchical graph attention networks [12]. Zhang et al. (2025) applied AI-driven sales forecasting in the gaming industry [13], while Yang (2025) implemented website internal link optimization using the Dijkstra algorithm [14]. Cheng et al. (2025) investigated the relationship between executive human capital premium and stock price volatility [15]. In urban planning and healthcare, Xu (2025) presented UrbanMod for text-to-3D city modeling [16], and Hsu et al. (2025) developed MEDPLAN, a two-stage RAG system for personalized medical plan generation [17]. Finally, Yuan and Xue (2025) proposed a multimodal information integration and retrieval framework based on graph neural networks [18].

2. RELATED TECHNICAL PRINCIPLES

2.1 Overview of VR Dynamic Interaction Platforms

The VR dynamic interaction platform is the core medium through which users engage with the virtual environment, typically comprising head-mounted displays, motion seats, and interactive controllers. At present, the dominant interaction method relies on controller button input: users press specific buttons to direct the virtual character's movement and orientation. While this approach is convenient, it inherently fails to replicate authentic bodily motion, making it difficult to achieve a true sense of presence and preventing the full realization of VR's immersive potential.

2.2 LiDAR Operating Mechanism

Light Detection and Ranging (LiDAR), as an advanced optical remote-sensing technology, acquires spatial information of target objects by emitting and receiving laser beams. Its core working principle is based on the Time of Flight (ToF) ranging method: the internal laser of the LiDAR emits pulsed laser light toward the target object; when the laser beam strikes the object's surface, it is reflected, and part of the reflected light is captured by the LiDAR's receiver. By precisely measuring the time interval from emission to reception and combining it with the speed of light c , the straight-line distance between the LiDAR and the target object can be calculated. To obtain the three-dimensional spatial information of the target object, modern LiDAR systems are typically equipped with multiple laser transmitter-receiver units and employ rotational or phased-array scanning to rapidly scan the surrounding environment at high frequency. Within an extremely short time, LiDAR can acquire a large number of discrete distance data points, which form point cloud data with three-dimensional coordinates (x, y, z) in space. Each data point contains not only the distance information between the target object and the LiDAR but also spatial coordinate information such as azimuth and elevation angles. By processing and analyzing these data points, the shape, position, and motion state of the target object can be accurately reconstructed. In this study, the human-back point cloud data acquired by LiDAR provides a rich and accurate raw information basis for subsequent body-turn detection.

2.3 Theoretical Foundations of Body Turn Detection

When the human body performs a turning motion, the relative distances between various parts of the back and an object behind it (a LiDAR sensor in this study) change in a regular pattern. When turning left, the left side of the back moves closer to the LiDAR, decreasing the distance, while the right side moves farther away, increasing the distance; conversely, when turning right, the distance on the left side increases and that on the right side decreases. Leveraging this characteristic, analyzing and processing the back-distance data captured by the LiDAR allows the turning direction of the human body to be determined, providing accurate input for motion control in VR interactions.

3. DESIGN OF A LIDAR-BASED BODY TURN DETECTION METHOD

3.1 System Architecture

The LiDAR-based body-turn detection system is composed of three main parts: the LiDAR sensor, the data acquisition module, and the data processing unit. The LiDAR sensor is responsible for collecting distance data from the human back; the data acquisition module preliminarily organizes and transmits the raw data obtained by the sensor; the data processing unit performs in-depth analysis and processing of the received data, ultimately outputs the judgment result of the human turning direction, and feeds the result back to the VR dynamic interaction platform to achieve interactive control.

3.2 Data Acquisition

In the data acquisition phase, the LiDAR detection area is precisely defined as the region on the human back from just below the shoulders to above the waist. This area exhibits relatively large and stable motion during body turns, effectively reflecting the characteristics of the turning action. To ensure full coverage of this core detection region, multiple preliminary experiments and ergonomic analyses determined that the optimal detection distance between the LiDAR and the human back is 0.5–1.0m. Within this range, on the one hand, the laser beams emitted by the LiDAR can sufficiently cover the back area from shoulders to waist, allowing the 4×4 formatted point layout to collect data that fully reflects back-turning movements; on the other hand, it avoids detection blind spots caused by overly close distances and the increased measurement errors that occur when the distance is too great.

During data acquisition, the LiDAR data refresh rate is set to 40Hz (matching the refresh rate of the v15315cx chip), scanning the detection area once per second; each scan yields 16 distance data points. Taking into account the natural characteristics of human motion and the platform's constraints on human–motion interaction, a normal turning speed (approximately $0 - 180°/s$) and angular range (left $60°$ – right $80°$) are defined, ensuring that the collected data can capture, in real time and dynamically, the changes in back distance under different turning speeds and angles, thereby providing sufficient and effective raw information for subsequent data processing and turn determination [1].

3.3 Data Processing and Analysis

After obtaining the raw data, the four column-wise data from left to right are averaged separately, yielding four data groups. The body's turning direction is determined by comparing the magnitudes of these four groups: when the average of the two right-hand groups is significantly higher than that of the two left-hand groups, a left turn is judged; when the average of the two left-hand groups is significantly higher than that of the two right-hand groups, a right turn is judged. By setting appropriate thresholds, misjudgments caused by slight swaying are eliminated, improving detection accuracy.

4. BODY-TURN SPEED CALCULATION AND PLATFORM CONTROL STRATEGY

4.1 Basic Idea

After using LiDAR to detect body turning, direct use of the detected angle as the true body-turning target is error-prone due to variations in human body shape, clothing material, and motion posture. Therefore, the numerical trend of the detection results must be combined to build a body-turning angle calculation model that better reflects reality. Meanwhile, when a VR platform rotates the user, frequent speed changes or excessive velocity may cause dizziness and discomfort, so a reasonable speed adjustment and limiting strategy is required to optimize user experience while ensuring real-time interaction.

4.2 Specific Methods

When calculating body-turning speed, first establish a time window that records the detected body-turning angles and the VR platform's current rotation angles within that window. Set an angle-difference threshold θ_{thresh} and a duration threshold t_{thresh} .

(1) Same-direction sustained turning judgment and speed control:

When the difference $\Delta\theta$ between the detected body-turning angle and the VR platform's current angle exceeds θ_{thresh} and this state lasts longer than t_{thresh} , the system determines that the user has a sustained turning demand in the same direction. At this point, according to the magnitude of the difference and its duration, the platform's rotation speed v is increased VR via a preset speed adjustment function $v = f(\Delta\theta, t)$. For example, a linear function $v = k_1\Delta\theta + k_2 t$ (where k_1 and k_2 are adjustment coefficients determined experimentally) can be used to match platform speed to the user's turning demand.

(2) Turning deceleration judgment and speed adjustment:

If $\Delta\theta$ keeps decreasing, it indicates the user is slowing the turn. Based on the rate of change of the difference $\frac{d\Delta\theta}{dt}$, the platform's rotation speed VR is reduced $v = g\left(\frac{d\Delta\theta}{dt}\right)$ via a speed adjustment function, such as an inverse proportional function $v = \frac{k_3}{\left|\frac{d\Delta\theta}{dt}\right| + \epsilon}$ (where k_3 is a coefficient and ϵ is a very small value to prevent division by zero), achieving smooth deceleration.

(3) Turning direction change judgment and control:

When the sign of $\Delta\theta$ changes—i.e., switches from positive to negative or vice versa—the VR platform immediately halts its current rotation and, according to the new turning direction, starts reverse rotation at a low initial speed to avoid user discomfort caused by abrupt direction changes.

5. EXPERIMENT AND RESULTS ANALYSIS

5.1 Experiment Design

The experiment employs the laser sensor chip v15315cx and the STM32F407ZGT6 microcontroller. The v15315cx is a high-performance ToF laser ranging sensor chip featuring multi-zone detection, capable of simultaneously measuring distance data from multiple targets to meet this study's requirement for 4×4 format points. Its ranging span is 40 mm–4 m, with ranging accuracy within 1m reaching ± 10 mm and a maximum data refresh rate of 50Hz , enabling rapid and precise acquisition of distance information for various points on the human back. In addition, the v15315cx supports the I^2C communication interface, facilitating data transmission with the STM32F407ZGT6 microcontroller [2].

The STM32F407ZGT6 microcontroller, based on the Cortex-M4 core, operates at up to 168 MHz, offers 1 MB of Flash memory and 192 KB of SRAM, and provides abundant peripheral interfaces—including ADC, SPI, and UART—for efficient acquisition and preliminary processing of v15315cx sensor data. It simultaneously executes body rotation speed calculations and platform control algorithms, satisfying the study's demands for data-processing speed and storage capacity.

The experimental environment simulates a real VR usage scenario by constructing a VR dynamic interaction platform in a quiet, low-interference indoor space. Twenty participants of varying ages and physical conditions were recruited to ensure the sample is representative.

5.2 Experimental Procedure

Participants wore a VR headset and stood on a VR motion platform, with their hands free to rest or perform other actions. The LiDAR, data acquisition system, and VR motion interaction platform were activated. Participants performed left- and right-turn movements in the virtual environment, including continuous turning, deceleration during turning, and changes in turning direction. LiDAR continuously collected distance data from the participant's back; the data processing unit determined the turning direction and calculated the turning speed, which then controlled the rotation of the VR platform while recording all experimental data.

5.3 Data Processing and Results Presentation

The raw data were analyzed to determine turning direction and calculate speed. Detection accuracy, platform speed adjustment response time, and user comfort scores were compiled for different participants under various turning actions. Results show the method achieved an average detection accuracy of 95% for human turning, with an average platform speed adjustment response time of 125 ms, effectively validating the feasibility and effectiveness of the approach. Figure 1 presents the relationship curve between body rotation angle and VR platform speed adjustment, visually demonstrating the performance of the detection and control method.

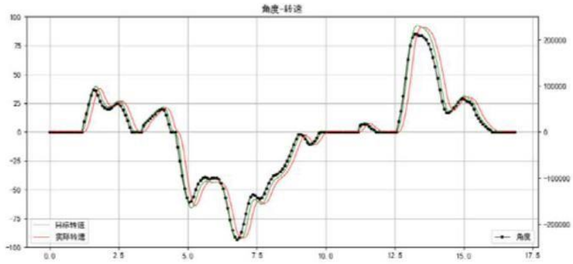

Figure 1: Body rotation angle and VR platform speed adjustment

5.4 Discussion of Results

The experimental results indicate that the LiDAR-based body-turn detection and speed calculation method successfully recognizes human turning and regulates VR platform speed, significantly enhancing the realism and comfort of VR interaction. However, several factors affecting performance were observed: deviations in LiDAR installation angle can introduce distance data errors, signal interference in complex environments can reduce detection accuracy, and certain clothing materials can affect data acquisition. Future research can address these issues by optimizing sensor installation, improving algorithmic anti-interference capabilities, and enhancing system stability and accuracy [3].

6. CONCLUSION AND OUTLOOK

This paper proposes and implements a LiDAR-based body-turn detection and velocity-calculation method. By using LiDAR to collect distance data from the human back and combining it with dedicated data-processing and velocity-calculation algorithms, the method effectively solves the problems of detecting human turning actions and controlling platform speed in VR dynamic interaction. Experiments verify that the approach significantly enhances realism, immersion, and comfort in VR intelligent interaction while freeing both hands, delivering a more natural and efficient user experience. The technology has broad prospects in the VR field. In gaming, it can be applied to large-scale multiplayer VR competitive games, allowing players to perform more flexible tactical maneuvers through real body turns. In education, it can provide more authentic interaction in virtual teaching scenarios, strengthening students' sense of immersion. However, the technology still faces many challenges, such as further optimizing sensor performance to reduce power consumption, refining algorithms to cope with complex environmental interference, and improving the universality of the velocity-calculation model. Future research will focus on these issues to perfect the technology and advance VR interaction toward greater intelligence and naturalness.

PROJECT

Shaanxi Province College Students Innovation and Entrepreneurship Training Program Project: Exploration of the Application of Artificial Intelligence to Support the Learning and Employment of Financial and Accounting Professionals (Project Number: PHDC2023030).

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