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Haptics-based force balance controller for tower crane payload sway controls

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ABSTRACT

Anti-sway control is an important issue affecting the safety and efficiency of tower crane operation, but the role of the human operator in this control loop is largely unknown. This paper proposes and designs a force-feedback based control method for anti-sway control. The system connects the tips of two haptic devices by a 3D printed pole and uses it to provide the balance status of the payload. The sway error is represented by the position and rotation changes of the pole. Meanwhile, the operator can use this haptic controller to adjust the payload pose by applying the counterbalance force to the pole. A human-subject experiment ($n = 34$) was performed to test the comparative benefits of the proposed method. The results show that the proposed haptics-based force balance control method outperformed the automatic method in both performance and subjective evaluations. The findings inspire the design of new human-in-the-loop approaches for heavy machine stability controls.

1. Introduction

Cranes are considered one of the most valuable and indispensable assets among all types of construction machinery (Al-Hussein et al. 2006). They are extensively utilized in construction projects to support critical activities such as heavy rigging and lifting [44]. Typically, two categories of cranes are popular in modern construction workplaces, including static cranes and mobile cranes [85]. Static cranes are permanent or semi-permanent mechanical machines fixed to the ground or structural platforms, which can lift and move the payload along a predefined path [33]. While mobile cranes, usually a hoisting mechanical structure mounted on a truck and crawler, are not restricted to a fixed path like a static crane and are capable of a "pick and carry" function [42]. Although mobile cranes are more flexible for mobility on job sites, they are often limited by the maximum payload. In contrast, static cranes, especially tower cranes consisting of a vertical tower/mast and an outstretched jib, are more capable of hoisting heavier payloads, and thus are more prevalent for major construction projects [43].

Crane operation is a highly professional and dangerous job due to the high skill barrier. Despite the tightened requirements on safety and advancements of crane operations, a large number of accidents related to crane operations have still been reported in the past two decades [61]. According to the American National Standards Institute (ANSI), there were 1125 tower crane accidents reported worldwide over a decade, resulting in >780 deaths. In the US, there were 27 crane-related fatal occupational injuries annually from 2003 to 2018 in the construction industry (Census of Fatal Occupational Injuries). The root cause of crane-related accidents is believed to pertain to the difficulty of manual operation methods of cranes. In the desired condition, transporting payload to the destination should be as fast as possible in order to improve productivity. Nonetheless, controlling the locomotion and movements of the payload is nontrivial for less trained human operators as it is an underactuated action in which the payload movement is not controlled directly but via the bridge and/or trolly in an indirect way [94]. Moreover, the payload is sensitive to acceleration and deceleration, causing unwanted motions like load sways and bouncing [2]. Dynamic environmental factors on most construction sites, especially changing wind loads, can also lead to payload sway [19]. Without anti-sway strategies, these unexpected payload motions could slow down operation speeds and thus degrade the payload transferring efficiency [45,47]. In addition, excessive sway angles also interfere with payload during loading and settling down operations [59]. Uncontrolled payload sways create a hazard for workers nearby and can cause damage to either the equipment, payload and the surroundings [46]. To achieve a precise payload positioning and sway control, crane operators usually need to go over extensive training, and have to continuously coordinate

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and communicate well with ground personnel such as riggers, signal crews and ironworkers during the whole operation process [20]. All these limitations make crane operations more mentally demanding than other construction equipment operations and thus, more prone to human errors [12]. Evidence shows that 43% of crane accidents resulted from human operator failures [36]. There is a pressing need to renovate crane operations, especially anti-sway methods, for the easier motor coordination and reduced mental load of the human operator.

Recently, efforts have been made to develop automatic anti-sway methods to tackle the payload sway problem. These methods utilize payload sensor data and sophisticated mechanical designs to suppress the unsolicited oscillations (e.g., [23,90,91]. However, most automatic anti-sway systems are designed for single-pendulum cranes (usually the overhead cranes) where the payload oscillation follows a more linear and modellable movement [93]. Using a simplified model of cranes maybe because of the computing complexity of incorporating more degrees of freedom. As such, lessons learned from the simplified models may not be readily transferrable to crane operation scenarios with more degrees of freedom, such as considering the two-pendulum three-dimensional sway commonly seen in tower crane operations. In addition, relying on an automated process of counteracting the sway may break the loop between the human operator's motor planning and the perceived feedback, causing an included perceptual-motor malfunction, i.e., the inability to effectively integrate perceptual information with the execution of voluntary behaviors [7,22,83]. Despite the advances in automatic anti-sway methods, there remains a need to explore a human-centric approach that will enable a more natural sensorimotor coordination in complex crane operations, especially in nowadays industries almost all cranes are controlled by human operators [80].

To fill these gaps, this study proposes a human-in-the-loop control approach for counteracting the sway problem in tower crane operations. Two haptic controllers are repurposed and connected with a pole forming a "seesaw" type of weight balance simulator. The payload sway status is mirrored synchronously as the loss of balance of the weight balance simulator. By holding the connection pole of the haptic controllers, a human operator can feel the large-scale payload sway as a weight balancing sensation in the hand. Then the control of the tower crane can rely on the human's natural ability to maintain balance to suppress the sway. As such, the human operator can react to the control tasks with a more integrated sensorimotor process. This study is expected to make the following theoretical and practical contributions related to tower crane operations. First, this study proposes and tests a novel sensory augmentation approach for anti-sway control, in addition to the existing automatic approaches. By designing and testing a unique haptic system for transferring the high-fidelity crane and payload dynamics data to the human operator in an intuitive way, the evidence collected from this study may inspire a new direction of research and technology development for heavy machine controls via sensory augmentation. Second, this study is expected to validate the effectiveness of human-in-the-loop in complex motion tasks such as machine operations. The crane operation literature has been focused on the automated approach to tackling difficult tasks. While there are ongoing arguments that human-in-the-loop or human-on-the-loop approaches are better fitted for similar complex tasks. The findings from the human-subject experiments should help confirm the comparable benefits of human-in-the-loop methods and highlight the applicable conditions of the automated approach. Third, this study is also expected to validate the efficacy of the digital twin approach in solving dynamic control problems and facilitating the corresponding investigation in a safe manner. To verify if the proposed haptics-based anti-sway control system can benefit crane operations, a digital twin model of a towel crane was built with a physics engine simulation of dynamics and kinematics in payload movement tasks. The high-fidelity reproduction of real-world physics will allow us and future researchers to test and examine new technologies without potential hazards. The analytics functions of the proposed digital twin system can enable real-time analysis of key performance outcomes such as collision avoidance and fine positioning, supporting a potential adaptive system in the future. The remainder of the paper introduces the point of departure, the design of the system, and a human-subject experiment to test the performance and cognitive benefits of the proposed method.

2. Literature review

2.1. Anti-sway suppression in crane operations

Payload sway is the excessive oscillating movement of the payload due to the fast locomotion of cranes, over-corrective actions of the operator, and environmental disturbances such as winds [92]. Once beyond a certain threshold, the payload sway can significantly affect the productivity of crane operations; and furthermore, pose a nonnegligible hazardous factor on both the workplace and human operators [77]. As a result, automatic anti-sway methods have been proposed to enable a more user-friendly sway suppression. These methods leverage reference models of the system states, such as the structure and kinematic features of the crane, to estimate the oscillating movement of the payload, and then apply a counteracting signal to suppress undesired movements [6]. The anti-sway control problem is generally solved using the optimal control theory, where the desired trajectory of a payload is maintained by minimizing the assumed function corresponding to the sway angle and its time derivatives, or to the energy consumption [30]. Conventional methods for solving the optimal control problem are employed to dampen the sway, including the Lyapunov-equivalence-based methods [10], feedback linearization [56], the Linear Quadratic Regulator (LQR) method [55], as well as the classic proportional–integral–derivative (PID) controllers [75]. Recently, the fuzzy logic [76], neural networks [35], evolutionary algorithms [1], or their combinations [88] have also been tested to address applications with a bigger uncertainty. Solving an optimal control problem also relies on the formulation models of the system states, i.e., how the deviation from the desired states is quantified. Knierim, et al. [38] proposed a flatness formulation to algebraically express the payload positions and control inputs in terms of their time derivatives from the desired destination. Then a counteracting supplement velocity term is added as a rest-to-rest maneuver along the planned trajectory. In contrast, Kim, et al. [34] modeled the system deviation as an energy term, which incorporated the regular momentum and thus could be more appropriate for applications when payload mass was important. Worth noting, machine learning models have also been tested to expedite the solution of the smoothing signals [35]. Depending on the timing of suppression, the automatic anti-sway methods can be further categorized into feedback (i.e., reactive) and feedforward (i.e., anticipatory) suppressions [63]. The feedback suppression continuously collects the system's state and reduces the effect of the unsolicited oscillation by adding a regulatory input to smooth the trajectory [23,90,91]. While the feedforward control predicts the oscillating movement based on a reference model and alters the command input signals proactively [25,28,87]. Recently, knowledge gained from the optimal control techniques has been translated into the industrial systems for automatic anti-sway controls. Representative systems include the ASLC (Anti Sway Load Control) system, the DynAPilot sway control system, the SmartCrane Anti-sway system, and the Rima system [30]. These industrial systems are designed to prevent the load swing based on information about control signals assigned by operator and measured value of the crane specifications such as rope length [30]. There are also solutions that are rope-length-independent, such as the Input Shaping™ that adjusts output frequency dampen out the harmonics of the system in an anticipatory manner instead of the reactive manner [65].

Despite the theoretical and practical advances in automatic anti-sway suppression, critical challenges still exist. First, most existing works model the payload sway as a single pendulum problem where the payload is assumed to anchor to a single pivot point for a periodical movement [93]. This simplified model assumption is mainly due to the computing difficulty in solving the nonlinearity problems, and the need for fast responses in practice. Nonetheless, in real-life applications, a tower crane often exhibits double-pendulum effects (from the trolly to hook, and from hook to payload), where the payload movement may demonstrate a more nonlinear behavior [86]. Most anti-sway methods rooted from the optimal control theory can hardly convert the nonlinearity into the original linear solutions [93]. To address this problem, there are several studies modeling crane systems as double pendulum problems [1,28,81]. But most models have simplified the payload as a point, assuming that the payload is directly attached to the hook by one rope, which cannot capture the real-world complexity of crane operation and require better modeling approaches. Second, the most commonly used automatic anti-sway suppression methods are based on the open-loop approach, where standard reference models of system states (e.g., the structure of the crane) are used to dampen the sway by controlling the acceleration and deceleration of the bridge and/or trolley motions through the crane's adjustable frequency drive (AFD) motion controllers (such as [69]). In contrast, the real-life tower crane sway may be better represented as a closed-loop problem, where severe external disturbances, parametric uncertainties and unmodeled uncertainties may not be captured by the reference models [17]. Closed-loop control strategies, such as Linear control [17], sliding modes control [31], and Intelligent Control [3], enabled the crane system to adjust its sway angles based on the feedback and is proved to be less sensitive to external disturbances, parametric uncertainties [54]. However, due to the input delay in the feedback loop, closed-loop systems often face delay problems [63]. In addition, the motions induced by the crane system to conduct anti-sway control could disrupt the human operator's intended crane operations [81]. A fully automated approach for suppressing sway breaks the integrity of the sensorimotor process of human operators, in which sensory information is coupled or with a corresponding motor response in complex motor tasks [21]. Such a human-out-of-the-loop approach may impair situational awareness in crane operations [20]. However, most automated strategies heavily relied on enabling machines in adaptive adjustments but ignored the impact on human operators from a human factors perspective. To improve overall crane operation performance, a human-in-the-loop approach for anti-sway control should raise attention.

2.2. Sensorimotor process in motor tasks

In complex motor tasks, humans rely on multimodal sensorimotor processes, such as the visual, auditory, and somatosensory (tactile and proprioceptive) stimuli, to make sense of the consequence of the initiated action [37,70,84]. When the perceptual ability is affected, i.e., initiating action without perceiving the immediate outcomes in a timely manner, the motor planning and feedback loop is broken, causing a perceptual-motor mismatch i.e., the inability to effectively integrate perceptual information with the execution of voluntary behaviors [41]. The perceptual-motor mismatch is often seen in clinical populations with impaired perceptual functions (especially visual, spatial, and tactile disorders), such as Asperger disorders, Parkinson's disease, and Developmental Coordination Disorders (DCD), etc. [32,60,73]. It is also seen when the perceptual ability is affected by external systems, such as caused by time delays in equipment operations [7,22,83], and human-automation interaction where human responsibilities are partially or completely replaced by an automated system [41,50,51]. As discussed earlier, most existing anti-sway suppression rely on automatic optimal control. It brings two potential issues with such a human-out-of-the-loop approach.

First, when automatic anti-sway systems are used, a similar perceptual-motor mismatch may be induced. It is because the outcomes from an initiated motion command by the human operator are continuously altered by an external automation system. For instance, in a recent study, the combined use of a PID controller and a sliding mode controller could reduce the sway by 84%; but it took at least 3 s to subside the sway trajectory because of the sensing, computing and reacting time [46]. As a result, the human operator may have to adopt a "move and wait" strategy as often seen in remote operations when delay presents [14]. Although the literature has not provided any evidence about how the automatic anti-sway systems affect the sensorimotor performance of the human operator, lessons have been widely learned in other automation applications, such as driver assistance systems [41,50,51]. For example, Mole, et al. [50] found that after as minimum as 10s of autopilot, the human driver could substantially lose the ability to calibrate optic flow that was critical for estimating the vehicle speed. De Winter, et al. [15] found that the use of adaptive cruise control (ACC) could significantly deteriorate the situational awareness of human drivers in peripherical tasks. As for lane-keeping functions, human driver's sense of haptic authority and satisfaction was found to decrease significantly due to the feeling of disturbance or interference when the assistive torque increased [57]. More critically, it has been widely reported that human drivers tended to recover slowly from the use of driver assistance technologies during driving tasks, and when these technologies failed, there would be significant risk implications [8,29]. The lessons learned from the driving automation literature suggest that the broadening use of automatic anti-sway systems may cause similar safety implications due to the affected sensorimotor processes of human operators.

Second, the increasing reliance on automatic anti-sway methods has limited the development of the haptic interface in crane operations that pertains to the haptic motor coordination of humans in motor tasks. At present, human operators mainly rely on visual channels to coordinate the motor actions in crane operations, i.e., the visuomotor coordination [24]. Because there are not yet effective solutions for force feedback stimulation to transfer the physical interaction information to the human operator, the haptic motor coordination is largely missing. In a recent study, Camponogara and Volcic [11] found that haptic motor coordination can help a more accurate perception about the size and position of the object, as well as trigger automatic and efficient handling corrections if a sudden perturbation causes a change. With that said, the benefits of human's haptic sensory channels have not been fully leveraged with the current crane operation methods.

2.3. Related works of haptic interface in crane operations

In recognition of the importance of engaging human operators in additional haptic motor processes for the anti-sway control of crane operations, the haptic control interface has been proposed. One of the earliest efforts was by Yoneda, et al. [89], where they developed a tactile device to generate vibrations of different frequencies depending on the deviation of the payload from the desired trajectory. By providing such a simple haptic cue, the operating speed was improved by 30% on average among six test subjects [89]. Following this early work, haptic systems that can provide enhanced haptic motor information are proposed. Takemoto [78] proposed a 2-DOF joystick that could tile in X and Y directions according to the sway vector in the corresponding directions. The degree of the joystick tilted in X and Y directions was driven by the sway angles. But the level of resistance remained the same. This system was improved by [67] to add force feedback based on the level of deviation. When the deviation was bigger, a stronger force would be felt based on a linear conversation formula. In the past decade, with the development of multi-morphological haptic devices, haptic controllers with more DOF were developed. Villaverde, et al. [82] leveraged a 3-DOF haptic controller to mimic the 3-DOF gantry crane; as such, the locomotion and kinematic states of the gantry crane could be mirrored with the haptic controller. They also proposed an impedance controller method to generate the force feedback in the haptic controller based on the dynamic positional information of the payload [82]. Similarly, Chu, et al. [13] applied a 6-DOF haptic device to simulate the control of a 3-DOF knuckle boom crane. They also integrated the force feedback in the haptic device based on a transformation matrix and Jacobian method to convert positional deviation into the corresponding forces on the tip of the crane hook [13]. Most recent studies also involve the use of the lightweight robot as the haptic controller for crane operations, such as [68].

Despite the proven benefits of these haptic interface designs for providing the required haptic feedback in crane anti-sway controls, the rendering of the high-fidelity force via haptic devices still heavily relies on the positional information. Impedance control and transformation methods based on the classic control theory are used to convert positional deviation into desired force feedback. In certain cases (such as [82]), simplified linear conversation formulas are used to simulate forces that may be intuitively reasonable but technically inaccurate. With the recent development of the physics engine, it is possible to rely on a model reference method to generate the accurate force feedback based on the complete reproduction of the physics processes occurring between the crane and the payload. This study will utilize physics engine simulation for force feedback simulation for payload sway, and collect data about if such an accurate and high-fidelity force simulation would improve the operator's performance and human function.

3. Proposed systems

3.1. Overview

This section describes the proposed haptics-based force balance method for anti-sway control. The Unity 3D physics engine and AGX Dynamics were used to build a Virtual Reality (VR) testbed including the tower crane modeling, physics simulation, haptic device programming, and data collection. We relied on the dynamic model parameters from a previous study [81] to ensure that the specifications of the simulated crane closely matched the parameters of a full-sized tower crane. The overall architecture of this integrated VR system followed our previous projects [95,96]. The main reason for using a simulation versus a real crane in the human-subject experiment is to ensure safety. A simulation study provides a better-controlled environment to test a novel control system without worries about potential safety hazards or deployment expenses. As our proposed haptics-based anti-sway control system is a brand-new design, hence testing this system with a real crane not only adds additional costs, but also brings operational risks to the operator and the tower crane itself. In this study, our main purpose is to validate whether such a haptics-based anti-sway control system can outperform other traditional anti-say control systems in the same operational environment. With the help of established dynamic models, real crane parameters, and the recent advances in physics engines, a simulation environment should have provided a realistic digital twin testbed for the purpose. To test how different control functions affect the crane operation performance in a contextual working environment, the human-subject experiment was performed. We built the VR-based real-time simulator for the payload positioning task, with the crane model mentioned before, an operation room located in the cabin, and a ZigZag exam field. The ZigZag exam field includes 34 poles and two fixed target circles as shown in Fig. 1. The pole contains physical properties and can be kicked down when the collision happens. In the VR simulator, the operator can see the movement of the payload through the first-person view from the cabin room. By changing the setting, the operator can easily switch control methods from different proposed controllers. The followings introduce the controller designs.

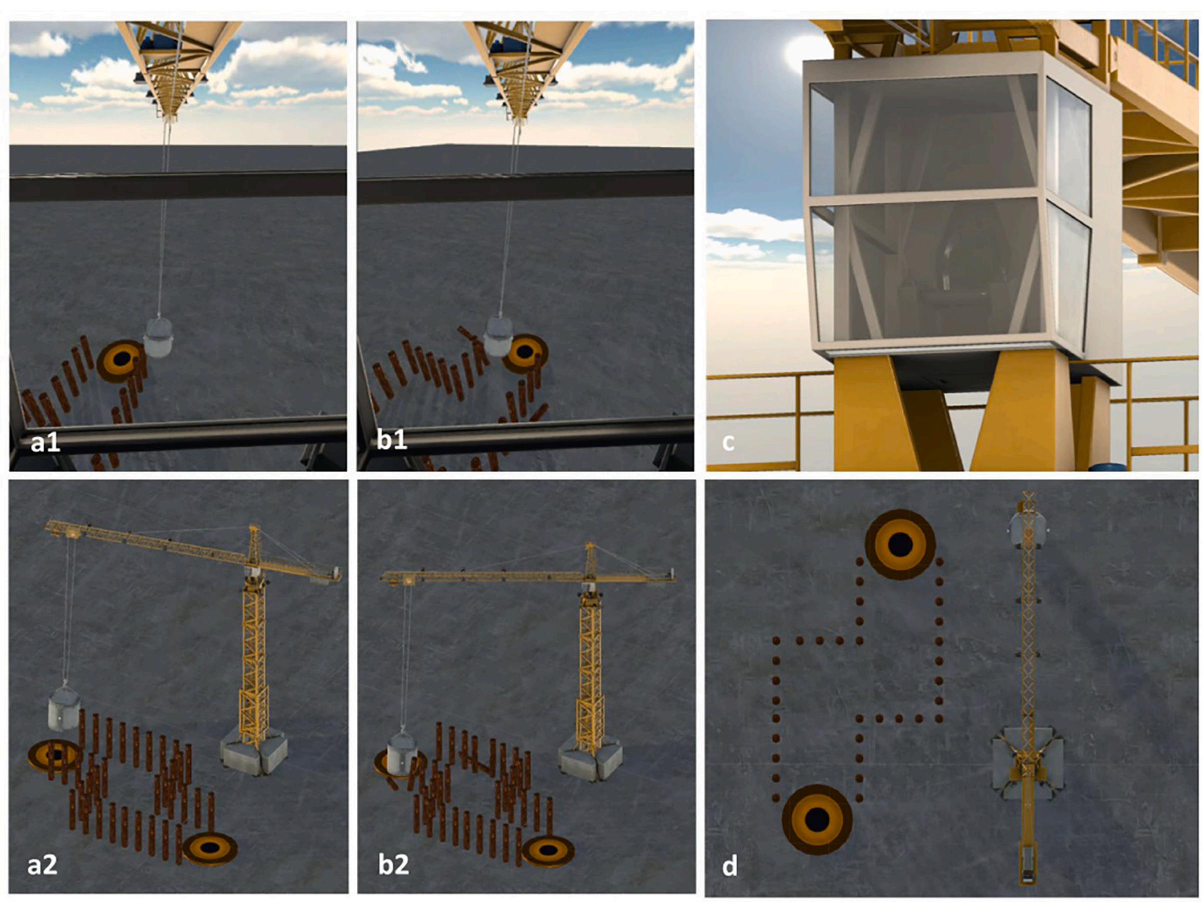

Fig. 1. VR-based real-time simulator. a, b are simulation results during crane operation when the load collision happens (b) / not happens (a), and a1,b1 are from the first-person view, a2,b2 are from the third-person view. c is the operation room that locates the VR camera. d is the Zigzag exam field from the top view.

3.2. Double-pendulum tower crane system

In order to amplify the physics fidelity of the model, i.e., reproducing a digital twin model of crane dynamics in a physically actuate manner, we utilized the latest physics engine technologies in our simulation. Specifically, we used the following strategies to provide a high-fidelity tower crane simulation. First, the parameters of our dynamic model of the tower crane were based on real data from a previous study (Vaughan et al. 2010). It ensured that the specific parameters of our model, such as movement speed, angles, and maximum ranges, reflected the true dimensional and operational parameters of a full-sized tower crane. Then, our simulation relied on the AGX Dynamics that modeled object dynamics directly based on the Newtonian mechanics, i.e., motions of objects were driven by forces like impacts, contacts, and friction following the real Newton laws. While in contrast, most VR systems model object dynamics based on positional controls, i.e., directly update XYZ based on the desired trajectory. Our force-based controls can ensure that the simulated behaviors of the tower crane capture real-world dynamics and environmental uncertainties. Based on the referenced parameters (Vaughan et al. 2010), we implemented the crane dynamic model for the anti-sway control system. A double-pendulum tower crane system with three degrees of freedom (DoF) was selected as the test model as shown in Fig. 2. This model composes serially connected components: a vertical column, an operation cabin, a 183-ft long jib, a mobile trolly, and a pulley system with suspension cables and hooks. The payload is linked to the crane by rigging cables. A hinge joint, which allows rotation (θ) around on specified axis, controls the slewing motion of the crane jib. A motorized prismatic joint, which allows translation along one axis, controls translation (r) of the trolley along the jib. To change the direction of the force needed to lift the payload and distribute that force over a distance, we designed a pully system with suspension cables and a winch that is able to pull in and feed out suspension cables (l). Unlike most previous studies that treat the payload sway as a single pendulum system, this study considers double-pendulum effects in the simulation. Our system used AGX to simulate ropes that have arbitrary stiffness for torsion, bend, and stretch and could report internal forces. Thus, it could mimic the ropes physics behaviors following real physics rules. We used four ropes to handle the payload which was closer to the real-world processes compared with using the payload as a single point. The payload is linked to the hook through four rigging cables which leave the load with three degrees of freedom in rotation.

After the tower cane model was built, the next step was to design the main control system (hereafter, main controller) that allows the human operator to operate the crane in the VR environment. The main controller enables the human operator to perform a series of moves, including swings (spinning the crane), trolley travels (moving the load along the jib), and hoists (raising the load with the rope). We integrated all the operation commands into one joystick. As shown in Fig. 2. two buttons on the joystick control the hoist (cable length l, left for up, right for down), the horizontal values of the joystick control slewing motion (rotation θ) and the vertical values of the joystick control trolley travel (movement r). With basic training, the participant without previous crane operation experience should be able to use this joystick to position a load anywhere within the crane's operating range. Fig. 3. shows how the load position changes during swings, hoists and trolley travel.

3.3. Closed-loop controllers

As mentioned earlier, the sway of the payload affects operability and increases the risks during the crane operation. One of the purposes of this study is to design anti-sway control functions to suppress the sway effects. In this study, we focused on the closed-loop control method as a solution, also known as the feedback control system, which leveraged

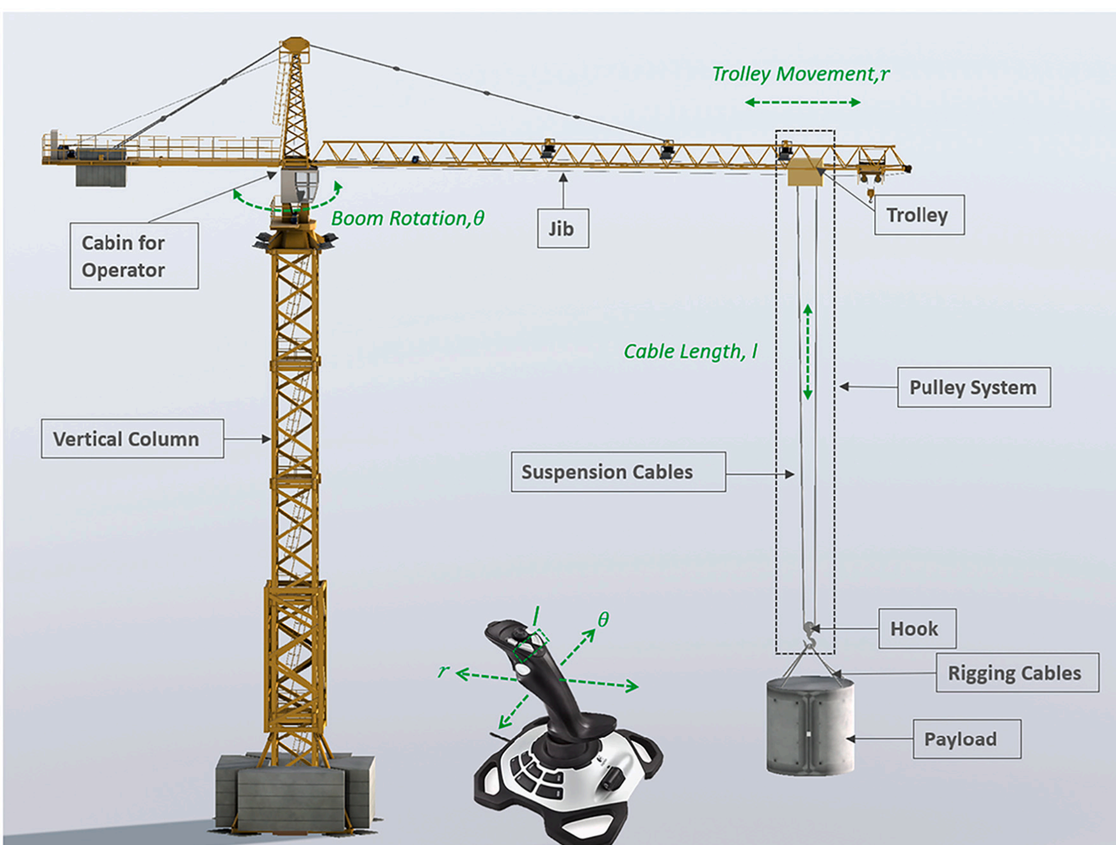

Fig. 2. Model of the double-pendulum tower crane and the main controller.

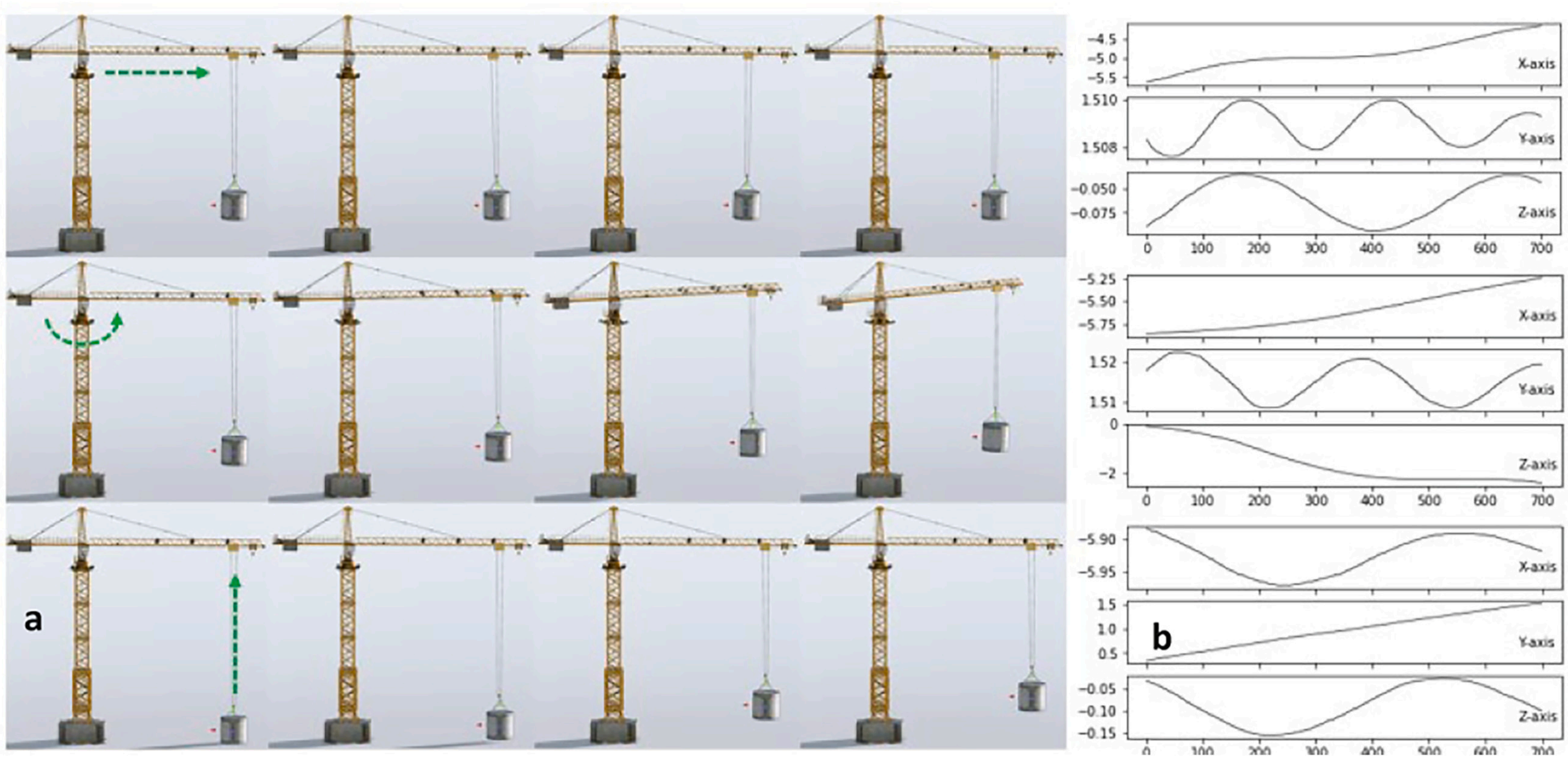

Fig. 3. Frames and data records from the simulation of the load position changes during trolley travel, swings, and hoists (from top to down). a. 3D simulation results. b. Corresponding movement records in x-,y-,z-axis separately.

the measurement and the estimation of the system states to achieve and maintain the desired output condition [48]. Hence the anti-sway control systems we proposed were designed to continuously monitor the sway error signals (the difference between the actual payload state and the reference state) and to make the necessary corrections to reduce the sway effects. The closed-loop control system was chosen because of the following reasons: 1) It is a commonly used control scheme for reducing payload sway that is less sensitive to a variety of parameters and thus is more robust to various scenarios [54]; 2) The advancement of sensing and simulation technologies is expected to facilitate the precise measurement of dynamic system states that are required for the closed-loop control; 3) the closed-loop control can incorporate uncertain human behaviors (such as actions of the human operator) as part of the control loop, and hence provides an opportunity to examine the implications of human-in-the-loop processes.

Our controller directly acts on the object instead of the crane system. The input signal is applied directly to the payload pose block. The goal of this study is to design and test a human-in-the-loop control system that can augment human performance and trust. As a result, the designed system should provide the most precise and high-fidelity object information to the human operator. Providing only crane dynamics information would not be sufficient to serve the purpose. Since there is no existing anti-sway controller that relies on the control of the payload, we simulated a theoretical control model that collected the position and acceleration of the payload object and provided forces in different directions on both sides of the payload. It can be a secondary stabilization system that can provide additional balancing force through additional motors attached to the jib, which can quickly correct the position deviation of the object to achieve the desired stability. The reasons we aim to examine this kind of payload controller are: 1) The haptic feedback for the human-in-the-loop design is based on the posture of the payload object, i.e., the sway error of the payload is represented by the position and rotation changes of two haptic devices. Force feedback based only on the crane system cannot capture the fidelity of data needed for the payload, and 2) we propose that the human operator should be able to simultaneously control the tower crane and the payload balancing. Fig. 4. illustrates the overall architecture of the closed-loop control methods. As it shows, the precise kinematic states are collected from the payload, such as the position and angular speeds. The collected data is sent to a controller, either realized by an automatic process or by a human-in-the-loop process, to minimize the deviation between the real-time kinematic states and the desired states. In our case, the desired states refer to a smooth trajectory of the payload movement without sway errors. To be noted, to simulate realistic work scenarios, human operator commands to the overall crane movement are also modeled, which adds additional complexity to our problem. As a result, the physics engine in Unity 3D is used to simulate the complex interactions between the payload and other components of the crane, including the jib and column.

Another purpose of this study is to compare three types of anti-sway control systems including a fully automatic system (based on the Proportional Integral Derivative, or PID controller), a reverse plugging system (i.e., manually applying a reverse torque to brake in advance via push button pendant) [40], and the proposed haptics-based force balance controller. Especially the haptics-based force balance controller is a novel closed-loop control method that features a human-in-the-loop process. It is to be compared with the other two widely used closed-loop anti-sway systems, i.e., the automatic system (PID controller) and the reverse plugging (push button pendant). This comparison is expected to provide evidence about the benefits of relying on a haptics-based human-in-the-loop process for anti-sway control. The following sections introduce the technical details of the three methods.

3.4. Method 1: the haptics-based force balance controller

Inspired by the human capability of balancing an object by hands, we proposed and developed a new anti-sway control system with a haptic controller as shown in Fig. 5.

This system connects the tips of two haptic devices by a 3D printed pole and uses it to provide the balance status of the payload. The sway error is represented by the position and rotation changes of the pole. Meanwhile, the operator can use this haptic controller to adjust the payload pose by applying the counterbalance force to the pole. To accurately restore the payload sway through the connected haptic device, we used Touch™ [79], a haptic controller which can provide 3-DOF force feedback in this study, as shown in Fig. 6. Then we defined two points A and B in the virtual world as the reference points corresponding to each of the haptic devices. The pole hence simulates the positional changes of l_{ab}, i.e., the line connecting points A and B, which cross the centroid of the load and is perpendicular to the lib. The relative position changes of A and B to the crane are used to drive the position changes of each tip (A' and B′) of the haptic device by force. To get the position reflections of points A' and B′ in virtual world coordinates, we conducted the calibration before the test which ensured the maximum range of A' and B′ to be the same as that of the A and B, as shown in Fig. 6.

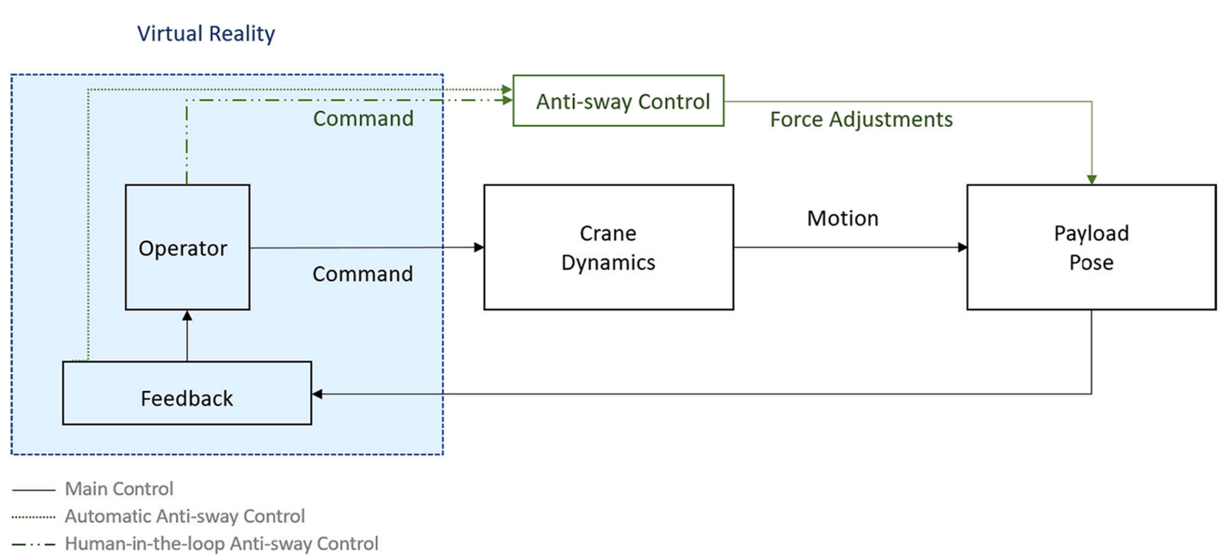

Fig. 4. Architecture of the closed-loop control methods for anti-sway control. (demo video: https://youtu.be/4A_r99cakqc)

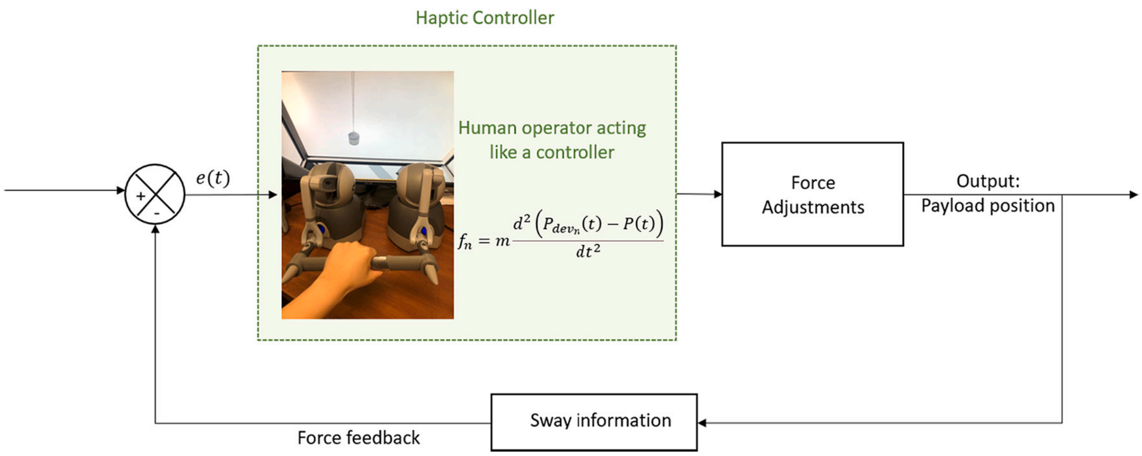

Fig. 5. Architecture of the proposed haptics-based force balance controller.

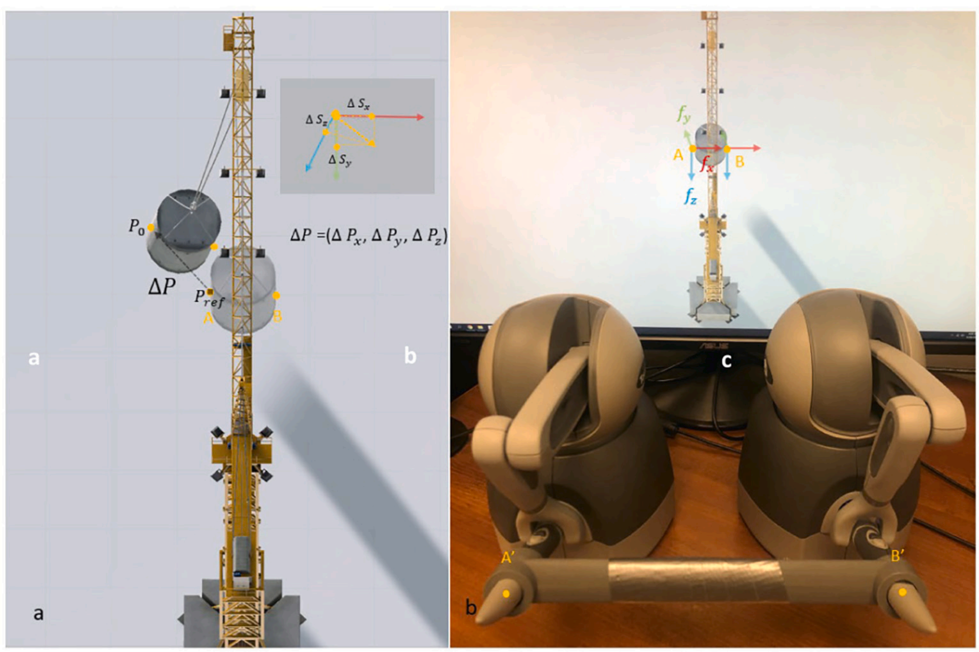

Fig. 6. Haptic controller (b) and the sway error (a).

After the calibration, we obtained the position values of points A' and B′ in the virtual world coordinates, which should be initially the same as the position values of A and B. The force feedback driving position changes of each tip is then implemented by the following equation:

$$F_n = m\frac{d^2\left(P_n(t) - P_{ref_n}(t)\right)}{dt^2} \tag{1}$$

where n indicates the coordinate axis's, $n \in \{x, y, z.\}$, m is the magnitude parameter to control the force level, $P_n(t)$ is the current load position in the n axis, and $P_{ref}(t)$ is the designed load position in the n axis. Hence, $(P_n(t) - P_{ref}(t))$ refers to the sway error in the n axis, and F_n is the force applied to the haptic device tip. According to this transformation, the sway errors in terms of position offsets can be transferred into force feedback delivered to the human operator through the haptic controller. To get real-time sway errors, we monitored and updated the offset distance in each axis between the desired position and the current position as shown in Fig. 6 a. An inverse transform function was applied to transform the position from world space to local space (relative to the crane) as follows:

$${}^{W}_{P}T = \begin{bmatrix} {}^{W}_{P}R & {}^{W}P_{B_0} \\ 0 \quad 0 \quad 0 & 1 \end{bmatrix}$$

$${}^{W}_{C}T = \begin{bmatrix} {}^{W}_{C}R & {}^{W}P_{C_0} \\ 0 \quad 0 \quad 0 & 1 \end{bmatrix}$$

$${}^{C}_{P}T = {}^{W}_{C}T^{-1}\,{}^{W}_{P}T = \begin{bmatrix} {}^{C}_{P}R_{11} & {}^{C}_{P}R_{12} & {}^{C}_{P}R_{13} & {}^{C}P_{P,x} \\ {}^{C}_{P}R_{21} & {}^{C}_{P}R_{22} & {}^{C}_{P}R_{23} & {}^{C}P_{P,y} \\ {}^{C}_{P}R_{31} & {}^{C}_{P}R_{32} & {}^{C}_{P}R_{33} & {}^{C}P_{P,z} \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{2}$$

where P indicates the position, R indicates the orientation, ${}^{W}_{P}T$ is the location matrix of the origin of the payload coordinate system measured in the world coordinate system, ${}^{W}_{C}T$ is the location matrix of the origin of the crane coordinate system measured in the world coordinate system, and finally, ${}^{C}_{P}T$is the location matrix of the origin of the payload coordinate system measured in the crane coordinate system. By this transformation, the sway errors are only counted by the local position offsets relative to the crane, ignoring its world space movements.

Once the operator sensed the sway error by the force feedback, they can then use the controller to counterbalance the sway effects. This countered force input is calculated according to the following equation:

$$f_n = m\frac{d^2\left(P_{tip_n}(t) - P_n(t)\right)}{dt^2} \tag{3}$$

where n indicates the coordinate axis's, $n \in \{x, y, z\}$, m is the magnitude parameter to control the force level, $P_{tip_n}(t)$ is the tip position in virtual coordinate axis n, $P_n(t)$ is the current load position in the n axis, and f_n is the countered force output applied in the n axis. Overall, this system allows the operator to sense the force changes caused by the movements of A' and B′, the load sway, and rotation estimation. Meanwhile, it also allows them to perform the anti-sway operation by applying an additional force to the payload through the haptic controller.

3.5. Method 2: reverse plugging controller via push button pendant

The reverse plugging method refers to applying a reverse torque braking to proactively correct the sway. It is a manual process preferred by experienced human operators. In our system, it is realized via a push-button pendant [58]. To provide a common control interface that operators might be more familiar with, we implemented an anti-sway controller based on a push-button pendant as shown in Fig. 7.

The sway error obtained in this system uses the same conversion function as the one used in the haptics-based control system. The sway information is converted into a numeric scale and displayed on a user interface (UI) panel fixed on the cabin window. This UI panel provided additional visual feedback information of sway errors to the human operator to level down the difficulty of the reverse plugging method for less experienced experiment participants. The input, i.e., sway errors $e(t)$ and the output, i.e., adjustment force $\boldsymbol{f_n}$, are the same as those in the haptics-based force balance control method. The difference is how the adjustment force is applied. For the haptics-based force balance control method, the adjustment force is given by the proposed haptic controller. In contrast, for the reverse plugging method, the adjustment force is given via the push button pendant. Under the push-button pendant control, commands generated by the human operator transmit from a push-button controller (realized as keyboard buttons in our case) to the force applied in the corresponding direction. As shown in Fig. 8, the six physical buttons correspond to adjustment forces in three directions, $n \in \{x, y, z\}$.

3.6. Method 3: automatic control via proportional integral derivative (PID) controllers

The last method we aim to test is the automatic anti-sway control via a Proportional Integral Derivative (PID) controller. As discussed earlier, the literature has demonstrated a great interest in developing and testing automatic anti-sway control methods based on optimization controllers. Among all optimization controllers, PID is pervasively applied to the crane system for control of the position and the payload's sway [63]. It is a technique that allows the crane to control the sway errors automatically with a set of suitable control parameters [71]. Although PID controller has been proposed for a long time, the efficacy of it in addressing simpler control problems has been well documented. For control problems with limited constraints and simpler targets, PID controllers usually have comparable performance with more advanced approaches. As a result, in the crane anti-sway literature, newer publications are still using PID controllers (e.g., [53,62]). We have also examined newer controllers and their pros and cons versus PID controllers. One example is the linear quadratic regulator (LQR). As a robust controller, LQR can produce lower steady-state errors than PID controllers, but with a bigger transition delay. For dynamic controls, such as tower crane anti-sway suppression, PID can provide a faster response with acceptable robust gains [5]. In other words, for the problem we aim to address, responsiveness shares a higher priority than the minimum steady-state errors, and thus, PID controllers are more preferred. Another popular controller is the model predictive control (MPC), which has a set of advantages compared to the PID, such as better results in peak overshoot percentage, integral of absolute errors and integral of time multiplied absolute of error [64]. It functions exceptionally effectively in complex systems. However, the algorithmic complexity of MPC usually requires a higher computational load, with a much higher number of control parameters [16]. It scarifies the computing efficiency for high precisions in results. Modeling the payload object in tower crane controls does not necessitate such a complicated model. In sum, PID is still one of the most commonly used control methods with a fast response time and acceptable state errors. For our problem, it satisfies the control needs as the payload object is only the item lifted by the tower crane, and a simple and fast-response controller is considered as a suitable choice.

The main goal of this study is to examine if human-in-the-loop approaches in anti-sway controls can obtain comparable performance results while leading to human factors benefits. Operators need to control the tower crane to move the object to the desired position as quickly as possible without colliding with obstacles. Depending on the sensors mounted on the object, the position, velocity, and acceleration information of the object can be retrieved. The output force of the controller also acts directly on the object. Therefore, the model of the PID

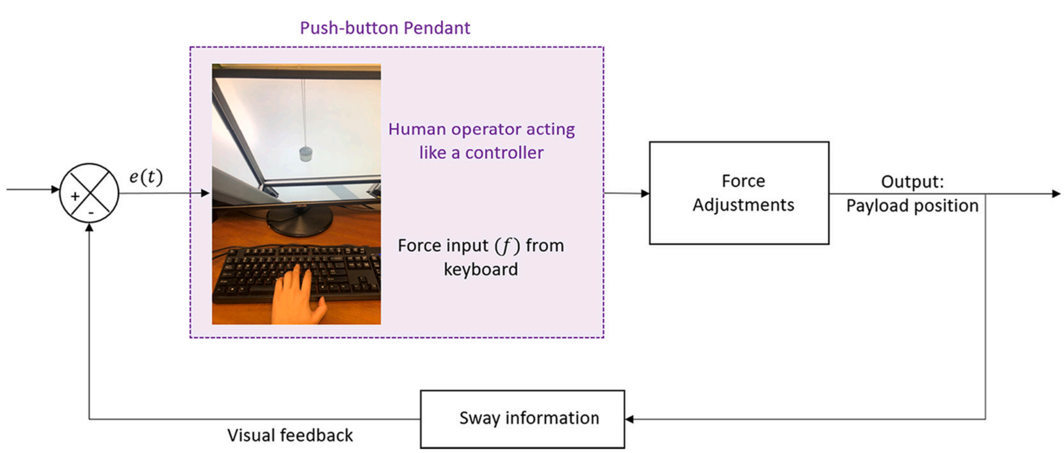

Fig. 7. Architecture of reverse plugging via push-button pendant.

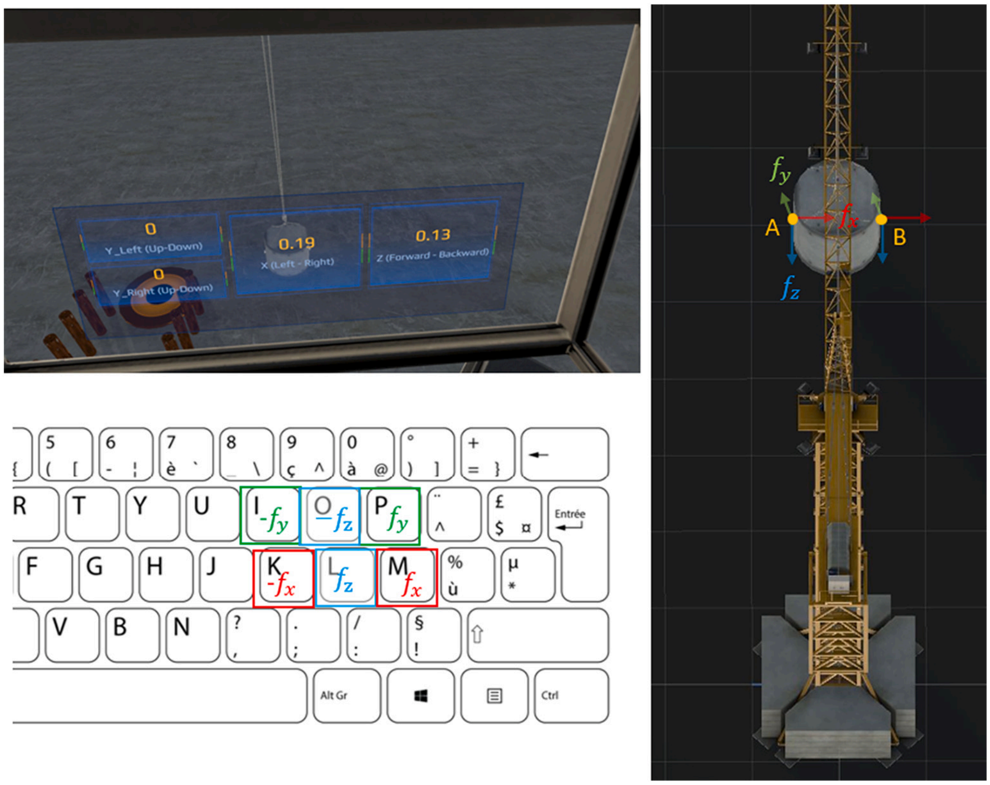

Fig. 8. Keyboard as the push-button pedant input for the reverse plugging method and the visual panel.

controller only affects the motion adjustment of the object and does not involve the control of the tower crane. Even though a PID controller is employed, the human operator still needs to control the direction, speed, and timing of the crane's movement to give the PID controller enough time to adjust the position of the load and thus avoid a collision. In order to evaluate the relative advantages of the proposed haptics-based force balance control method, we developed and implemented a PID controller for controlling the sway angle by applying optimized force adjustments on the payload. A block diagram of the PID controller is shown in Fig. 9.

The PID controller is implemented by the following equation:

$$f_n(t) = k_{p_n} e_n(t) + k_{i_n} \int_0^t e_n(t)dt + k_{d_n} \frac{de_n(t)}{dt} \tag{4}$$

where n represents the coordinate axis, e_n is the sway error in the n axis, and $f_n(t)$ is the optimized force output applied in the n axis. In our case, the optimized parameters of the controller are tuned by the particle swarm optimization (PSO) algorithm [72]. Since the dimension of the search space is only three (K_p, K_i, and K_d), a fixed weight is assigned for the inertia parameter ($W = 1$). Optimized PID parameters for this study are $K_p = 2.463$, $K_i = 1.812$, and $K_d = 0.742$.

To test the efficiency of the PID controller, we compare the sway motion results with and without the PID controller. In both conditions, we place the initial position of the object in the same midair and let it fall naturally. The reason for such a superior result is that our PID controller considers a theoretical scenario for directly acting on the payload object instead of the crane system. We consider a secondary stabilization system that can provide additional balancing force through additional motors attached to the jib, which can quickly correct the position deviation of the object to achieve the desired stability. Fig. 10. shows the comparison of sway motion results with and without the PID controller.

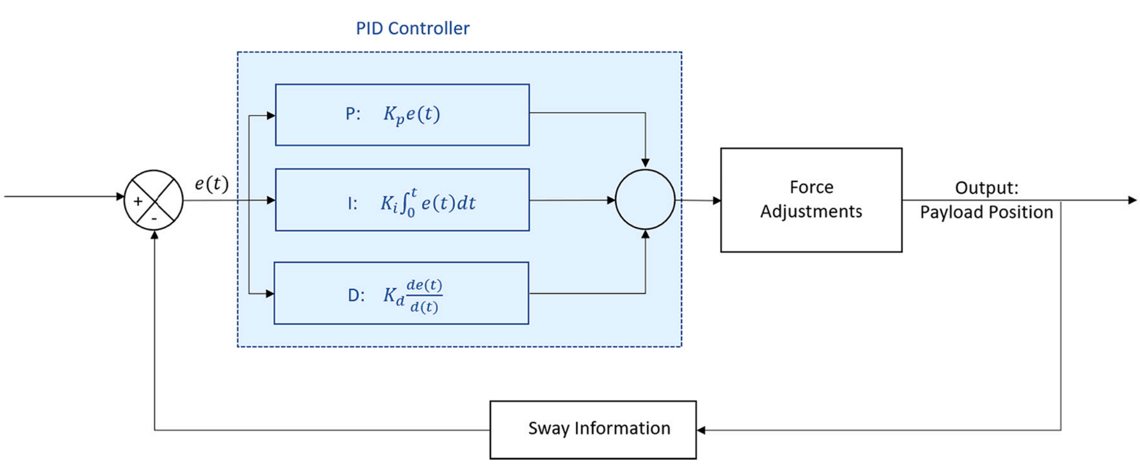

Fig. 9. Architecture of the Proportional Integral Derivative (PID) controller.

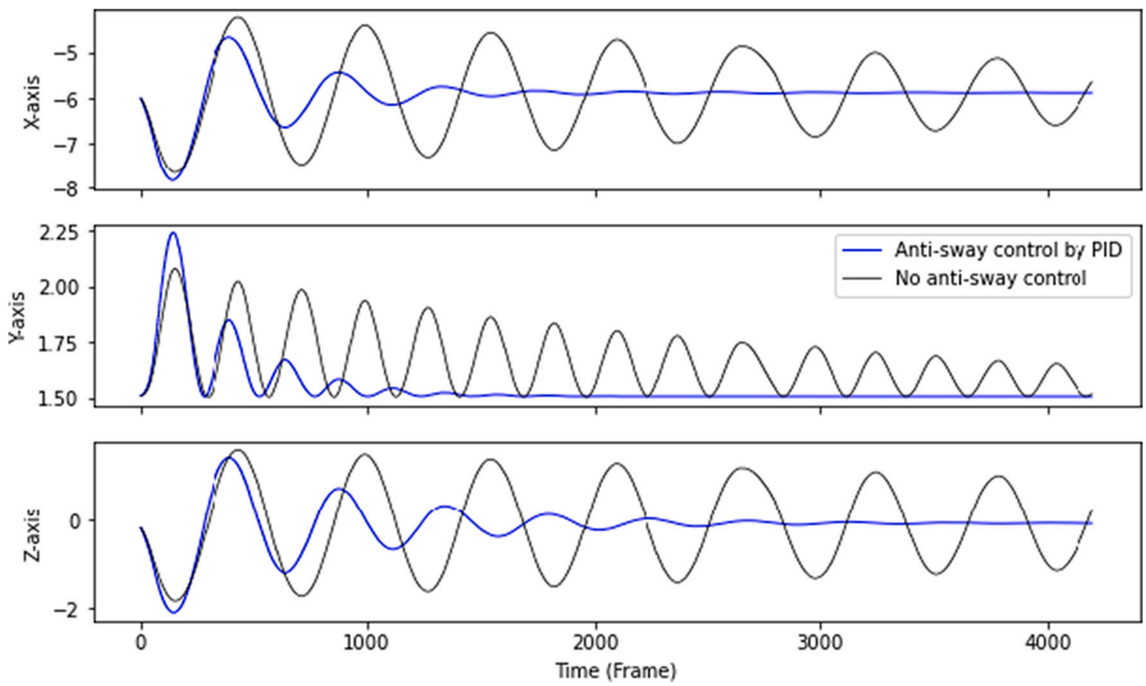

Fig. 10. Example results of automatic anti-sway control via a PID controller.

We observed convergence results in all directions, i.e., the line with the PID controller becomes smooth in a more quick way, which confirmed the effectiveness of the PID controller in suppressing the sway effects.

4. Human subject experiment

4.1. Participants

To test the effectiveness of the proposed method, we performed a tower crane material handling experiment in VR. We recruited a total of 34 participants (female = 18) aged between 19 and 30 years old. All participants reported that they were right-handed and did not have any known motor disorders or a history of neurological abnormalities. The study was conducted with the ethical approval of the ethics committee at the University of Florida (IRB# 202200781). Participants gave their written informed consent before participating in the study. They were requested to perform the crane operation task in a sitting position, which is considered safe and comfortable in most similar VR studies. Fig. 11. shows the scenario of a participant during the experiment.

4.2. Experiment procedure

The experiment involved the Zigzag Corridor task of operating a tower crane for material handling in VR. It followed a within-subject experimental design with four conditions, namely Control, Haptic, Reverse, and Automatic. Under the Control condition, participants could only rely on visual cues to operate the crane, similar to what the real-world crane operators' practice. Under the Haptic condition, participants could rely on the proposed haptics-based force balance controller to perceive the sway errors and to counterbalance the sway. Under the

Fig. 11. A participant in the tower crane material handling experiment under four conditions. a. Control. b. Reverse. c. Haptic. d. Automatic

Reverse condition, participants were asked to use the push-button pendant (i.e., keyboard) to exercise the reverse plugging braking when a sway was sensed. Finally, under the Automatic condition, the sway would be automatically suppressed by the PID controller. In all conditions, participants were able to use the joystick to control the overall movement of the tower crane and the jib, and hence the haptic controller and automatic mechanism were designed purely for the anti-sway control.

Each subject was required to repeat the crane operation task under each condition two times to collect a more stable performance and behavioral data, in case unintended errors or adaptation to the system distorted the results. The sequence of tasks under different conditions was shuffled to eliminate the learning effects. The whole procedure for each subject was as follows: 1) Training session: participants were trained on how to operate the crane within the VR environment under four conditions; 2) Tasking session: participants were required to perform the crane operation task twice under one of the four experimental conditions; 3) Rest and Survey session: participants took a brief rest and answered questionnaires in this session. Then participants repeated the procedure for the remaining conditions.

The crane operation task for all conditions was the same, which was designed according to the traditional crane operator practical exam standards (national commission for the certification of crane operators) [52]. Participants could freely operate the crane via the proposed control system and other methods. As shown in Fig. 12, for the task, they were first asked to lift the payload from the original point and then place the payload at the Start Point. Once the payload stabilized, the participant was then required to lift it again and do negotiate the zigzag corridor with the load task. The task was marked as completed when the payload reached the End Point. During the whole task period, the participant had to practice lifting, swinging, booming up or down, and hoisting up and down operations to guide the load through the Zigzag corridor without touching the ground or boundaries. Reproducing a desired zigzag navigation was considered an essential part of the crane operation qualification exam as it can evaluate the operator's capability of controlling sway effects and accurately positing. As a result, this task is a practical evaluation to access human operation performance with different control methods. The experiment lasted for about one hour in total, including time for VR device placement, device calibration, participant instruction and training, tasking, and post-survey.

5. Data analysis

To obtain a holistic evaluation of participants' task performance and functional data under four conditions, both subjective and objective metrics were collected. In terms of the subjective evaluation, we used NASA TLX questionnaires [26] to access the workload levels, and a trust survey [49] to estimate the trust levels of the operator to the anti-sway control systems (Haptic, Automatic, and Reverse). The objective evaluation took both task completion time and operational accuracy into consideration. The accuracy of operation performance was analyzed with respect to three different errors (pole collision, positioning and trajectory). The purpose of this evaluation was to examine whether there were any significant task performance differences among conditions, which can help demonstrate the difference between automatic control and human-in-the-loop control. The one-way ANOVA at each metric between trials was performed to ensure that no significant trial differences at each metric would affect our further analysis. Then the repeated-measures ANOVA was performed to test for differences in each metric by the four different conditions. Reported *p*-values were calculated by follow-up, two-tailed Bonferroni-corrected pairwise comparisons. To be noted, there were no significant differences between the first trial and second trial for any condition or any metrics.

5.1. Task completion time

To access whether anti-sway controllers accelerated the task accomplishment, we compared the completion time among the four conditions. The task completion time was calculated as the amount of time required from the beginning when the payload was firstly lifted and to the end when the payload arrived at the End Point.

As shown in Fig. 13. we observed significant changes in completion time among four conditions (repeated-measures ANOVA, $F = 23.00$, $p < 0.001$). Pairwise comparisons revealed statistically significant differences in Control-Haptic ($p < 0.001$), Control-Automatic ($p = 0.003$), Control-Reverse ($p = 0.027$) Haptic-Reverse ($p < 0.001$) and Automatic-Reverse ($p < 0.001$). No statistically significant difference was observed in Haptic-Automatic. Overall, the use of the haptics-based force balance controller led to the best performance in terms of task completion time. And using the reverse plugging controller caused the worst performance in terms of task completion time.

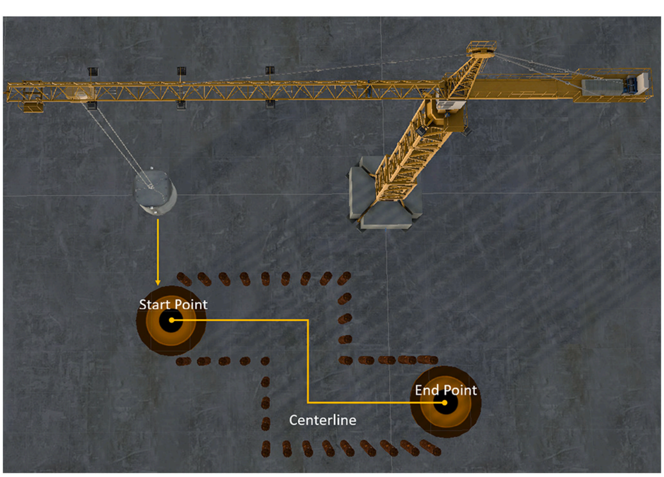

Fig. 12. Tower crane Zigzag Corridor task for the test; adapted from [52].

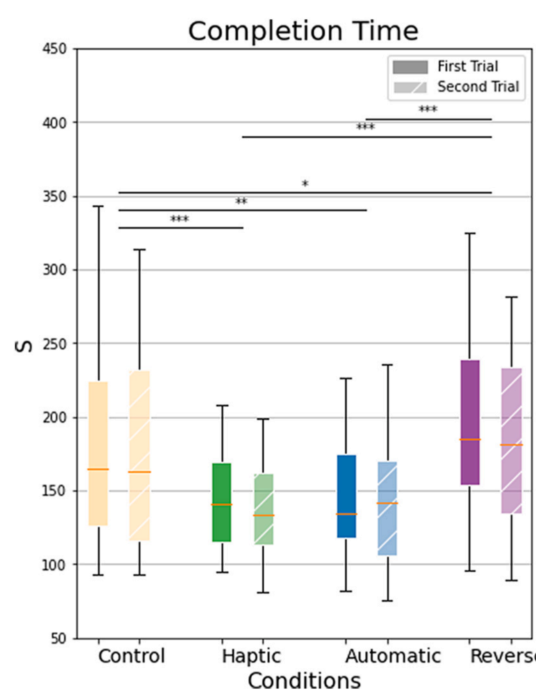

Fig. 13. Task completion time comparison, * indicates statistically significant change (*$p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

5.2. Trajectory accuracy (symmetrized segment-path distance)

The Zigzag Corridor test requires the crane operator to carefully move a load within a limited range. The comparison between the payload trajectory during the task and the centerline of the ZigZag indicates the operational offset errors. To access this offset error, Symmetrized Segment-Path Distance was chosen in this study as it can compare both the shape and physical distance between two trajectories as a whole, regardless of their time indexing or the number of locations that compose them [9]. This method is widely applied in research related to vehicle and human movement analysis [74] and is considered suitable for our study purpose. According to [9], the trajectory accuracy can be quantified as follows:

$$D_{SPD}\left(T^e, T^b\right) = \frac{1}{n_e}\sum_{i_e=1}^{n_e} D_{pt}\left(p_{i_e}^1, T^b\right) \tag{5}$$

$$D_{SSPD}\left(T^e, T^b\right) = \frac{D_{SPD}\left(T^e, T^b\right) + D_{SPD}\left(T^b, T^e\right)}{2} \tag{6}$$

where T^e is the trajectory recorded in the experiment from the four conditions and T^b is the standard route (the centerline of the ZigZag) as shown in Fig. 12. $D_{pt}(p_{i_e}{}^1, T^b)$ is the minimum distance from point p of T^e to the trajectory T^b, which is measured by Hausdorff distance [27] in this study. $D_{SSPD}(T^e, T^b)$ is symmetric segment-path distance which takes the average value of the distances from both T^e to T^b and T^b to T^e. We calculated D_{SSPD} of each trajectory record from the four conditions to the standard route and then used it as the metric of Trajectory Accuracy. The lower D_{SSPD} value means fewer offset errors.

We observed significant differences in Trajectory Accuracy among the four conditions (repeated-measures ANOVA, F = 38.07, $p < 0.001$). As shown in Fig. 14, the y-axis is the scale value measured by Symmetrized Segment-Path Distance. A smaller value means that the object's trajectory is closer to the ZigZag trajectory as a whole. There were significant differences in Control-Haptic ($p < 0.001$), Control-Automatic ($p < 0.001$), Control-Reverse ($p = 0.003$), Haptic-Reverse ($p < 0.001$) and Automatic-Reverse ($p < 0.001$). However, no significant statistical differences were found in Haptic-Automatic again. Overall, the use of the anti-sway controllers led to better performance in terms of payload movement trajectory. And the use of the reverse plugging controller caused the worst performance in terms of the movement trajectory among anti-sway controllers.

5.3. Collisions

According to the NCCCO practical exam guidelines, moving the pole base off the marking line or knocking the pole down should be counted into point deductions. To achieve the best performance, the operator should be proactive with their crane movements to avoid the collision. Therefore, we counted the number of fallen pole bases as one of the task performance indicators.

Figure 15 shows the result of collisions. The y-axis is the collision times of each condition. Smaller values mean fewer collisions with obstacles. Significant changes were observed in Collisions among four conditions (repeated-measures ANOVA, F = 69.86, $p < 0.001$). The results indicated there were significant differences in all pairs including Control-Haptic ($p < 0.001$), Control-Automatic ($p < 0.001$), Control-Reverse ($p = 0.001$), Haptic-Automatic ($p = 0.001$), Haptic-Reverse ($p < 0.001$) and Automatic-Reverse ($p < 0.001$). Till now, we found that even though there was no significant difference between the Automatic and Haptic in Completion time and Trajectory distance, the Automatic and Haptic were significantly different in terms of Collision. A possible explanation is that the overall anti-sway control performance of Automatic and Haptic conditions was much similar, but with haptic control, participants could perform better at positioning the payload within a more restricted area. To validate this possibility, we also evaluated the positioning accuracy at the Start Point and the End Point, as follows.

5.4. Placing accuracy (Euclidean distance)

To get the placing accuracy, we recorded the location of the payload when it reached the target point (Start/End). And then we calculated the Euclidean distance between the payload location and the center of the target point as the follows:

$$d\left(p^l, p^t\right) = \sqrt{\left(p_x^l - p_x^t\right)^2 + \left(p_y^l - p_y^t\right)^2} \tag{7}$$

where p^l is the recorded position of payload from each trail and p^t is the central position of the target point. A larger $d(p^l, p^t)$ value indicates the bigger positioning error. Then we used $d(p^l, p^t)$ as the placing accuracy value and did the further comparative analysis. As the placing difficulties of reaching the Start Point and End Point were dissimilar, we calculated the placing accuracy of the Start Point and the End Point separately.

Figure 16 shows the result of start point placing accuracy. The y-axis in Fig. 16 is the Euclidean distance of the placed object from the start center point. A smaller value means that the placing position is closer to the center point. The results of the Start Point placing accuracy show that there were significant differences in pairs including Control-Haptic ($p < 0.001$), Control-Automatic ($p = 0.001$), Control-Reverse ($p = 0.026$), Haptic-Reverse ($p = 0.004$) and Automatic-Reverse ($p = 0.029$). But there is no significant difference in the pair of Haptic-Automatic ($p = 0.174$).

Figure. 17 shows the result of the End point placing accuracy. The y-axis in Fig. 17 is also the distance of the placed object from the start center point, but the point is the end center point. In terms of the End Point placing accuracy, we found significant differences in all pairs, including Control-Haptic ($p < 0.001$), Control-Automatic ($p < 0.001$), Control-Reverse ($p = 0.003$), Haptic-Automatic ($p = 0.015$), Haptic-Reverse ($p < 0.001$) and Automatic-Reverse ($p = 0.043$).

5.5. Subjective evaluation

We were also interested in understanding how the different anti-sway control methods affected the subjective evaluation of workload and the Trust in Automation (TiA) among participants.

The NASA TLX questionnaire with six sub-scales was used to evaluate the workload levels from different perspectives. We used the total score of sub-scales as the final workload score. The y-axis in Fig. 18 is the workload score from different perspectives. A higher value means a higher cognitive load level during the experiment. The results as shown in Fig. 18. indicated that there were significant differences in all pairs including Control-Haptic ($p < 0.001$), Control-Automatic ($p < 0.001$), Haptic-Automatic ($p = 0.001$), Haptic-Reverse ($p < 0.001$) and Automatic-Reverse, except for the pair Control-Reverse ($p < 0.001$). In general, the use of the proposed haptics-based force balance controller represented the most desired result.

To understand the perceived reliability of the anti-sway control system, we also applied a six-item Trust Scale questionnaire inferred from the previous study [49]. This questionnaire is one of the most common surveys for capturing human tendency to trust automation and to contextual TiA behaviors [39]. We used the overall scores as the TiA result. If a person relies more on the system, he/she tends to give a higher TiA score. The y-axis in Fig. 19 means the score of trust level. A higher value means people are more inclined to trust this control system. In terms of the subject's trust level in the anti-sway control system, we observed significant differences as shown in Fig. 19. among all pairs including Haptic-Automatic ($p = 0.003$), Haptic-Reverse ($P < 0.001$), Automatic-Reverse ($P < 0.001$). In general, participants showed the highest level of trust toward the proposed method.

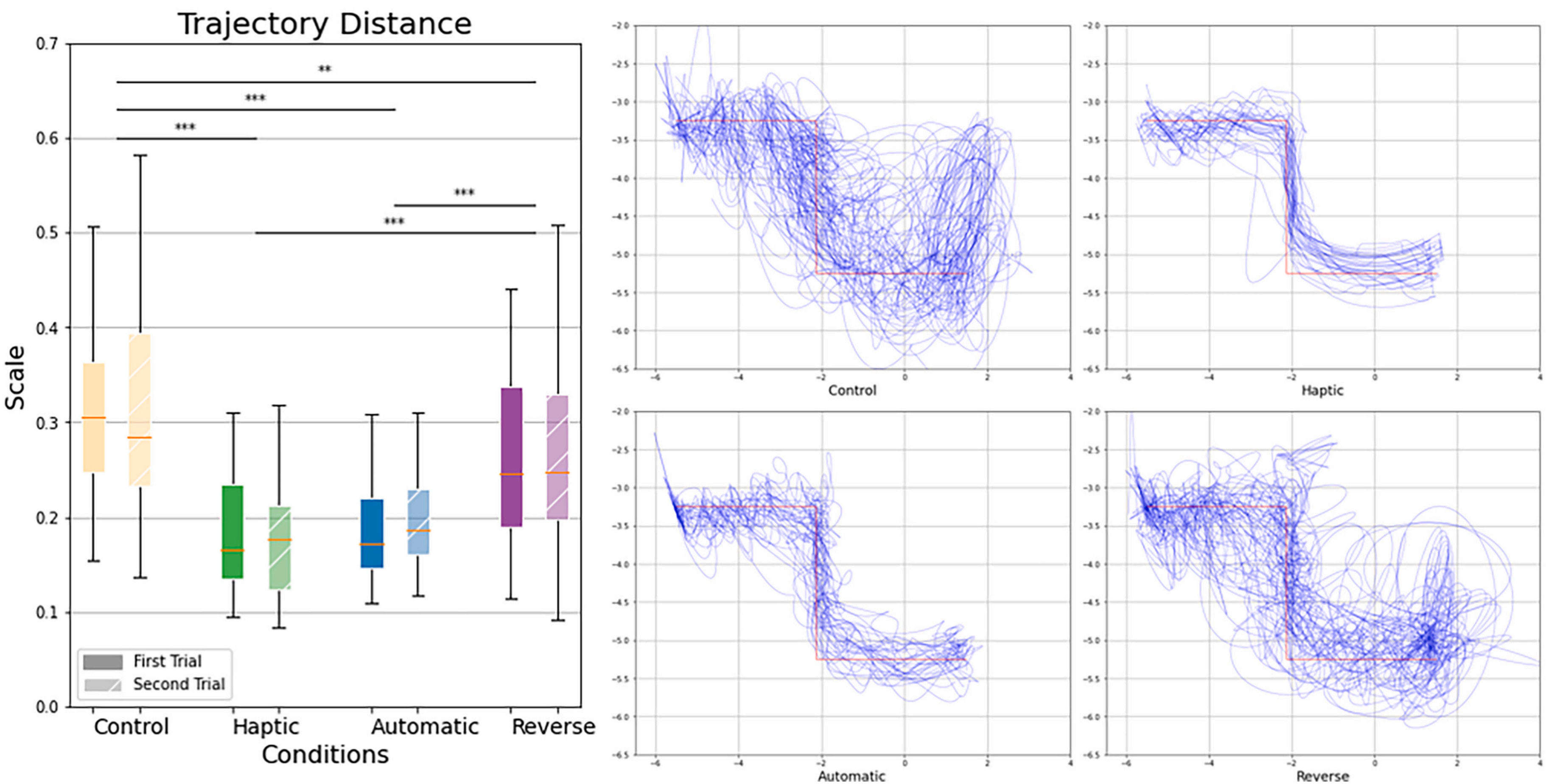

Fig. 14. Trajectory accuracy comparison and trajectories of participants recorded from four conditions, * indicates statistically significant change (*$p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

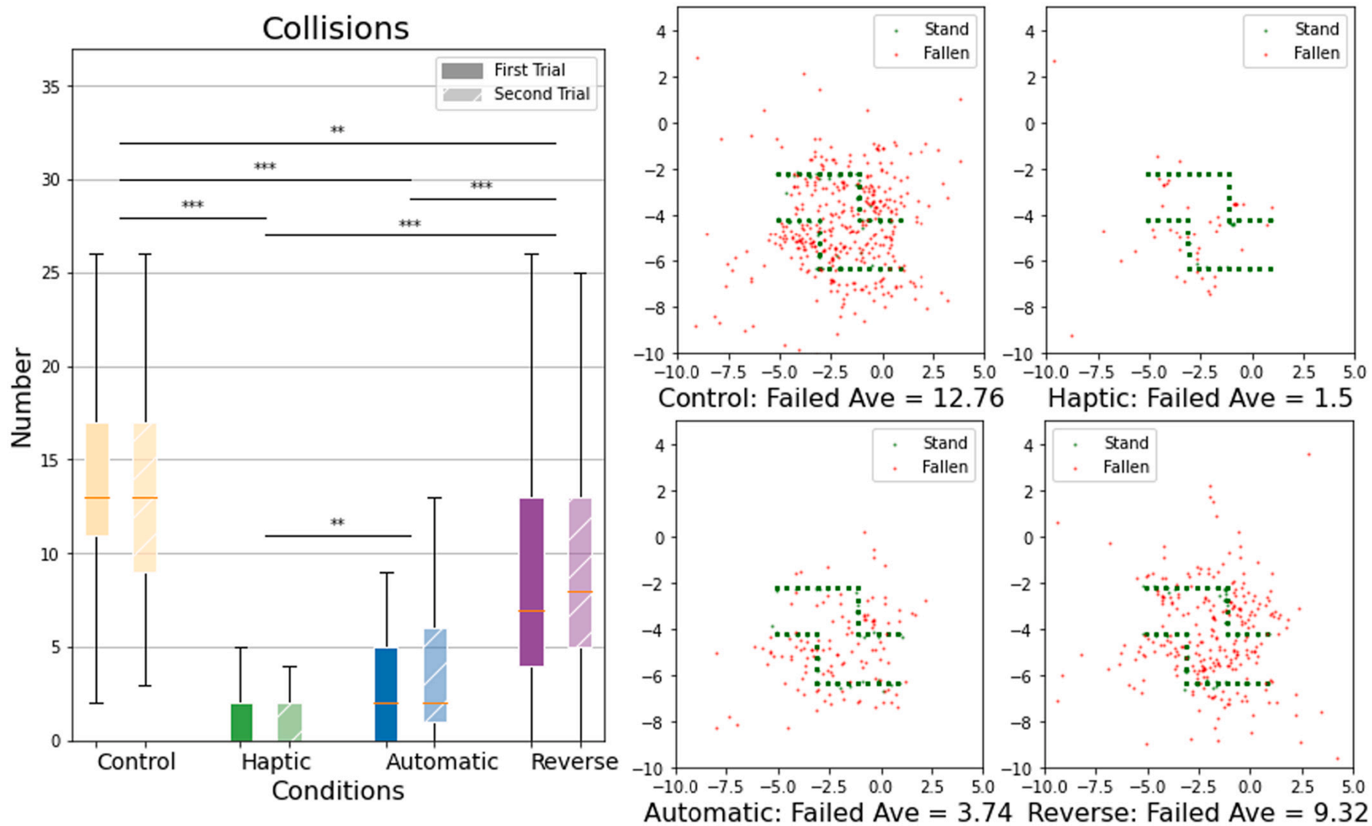

Fig. 15. Collision incidents comparison and the distribution of poles recorded from four conditions, * indicates statistically significant change (*$p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

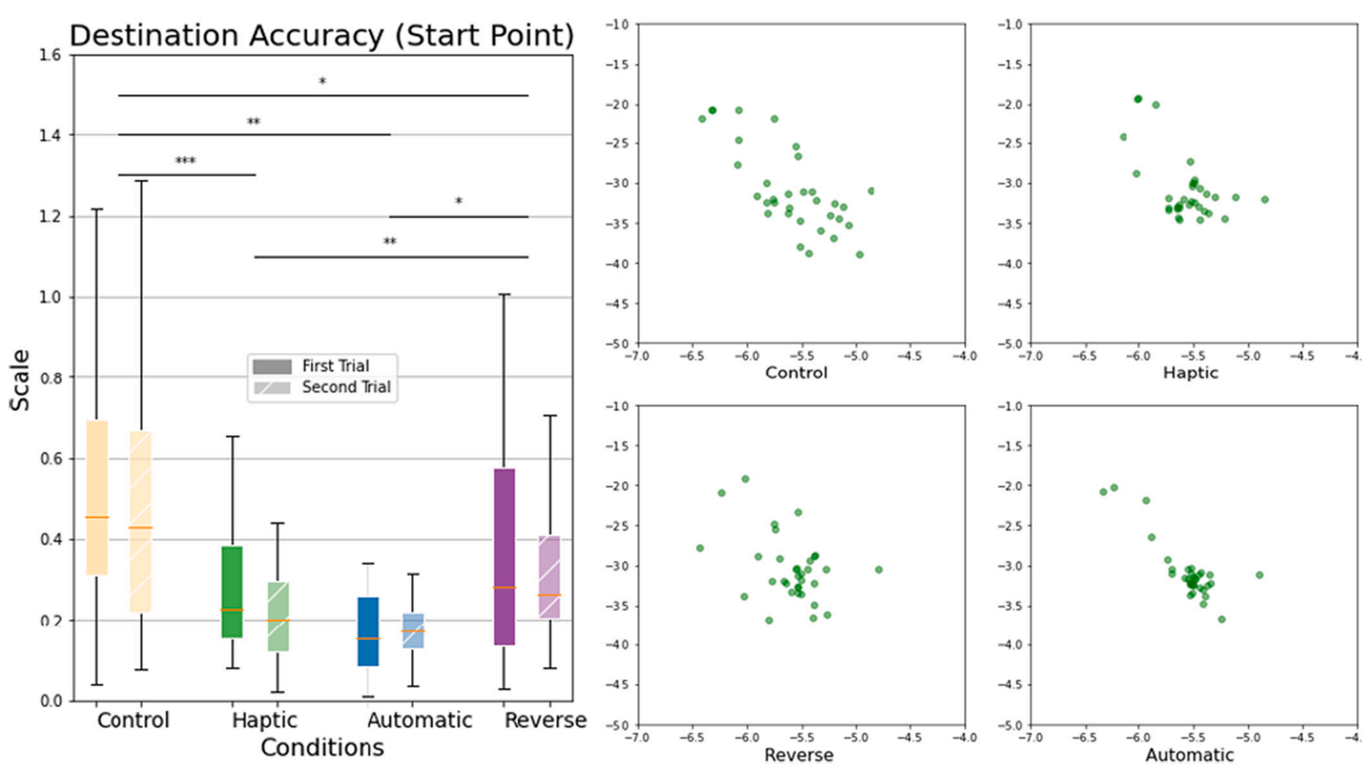

Fig. 16. Placing accuracy at Start Point and the distribution from four conditions, * indicates statistically significant change (*$p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

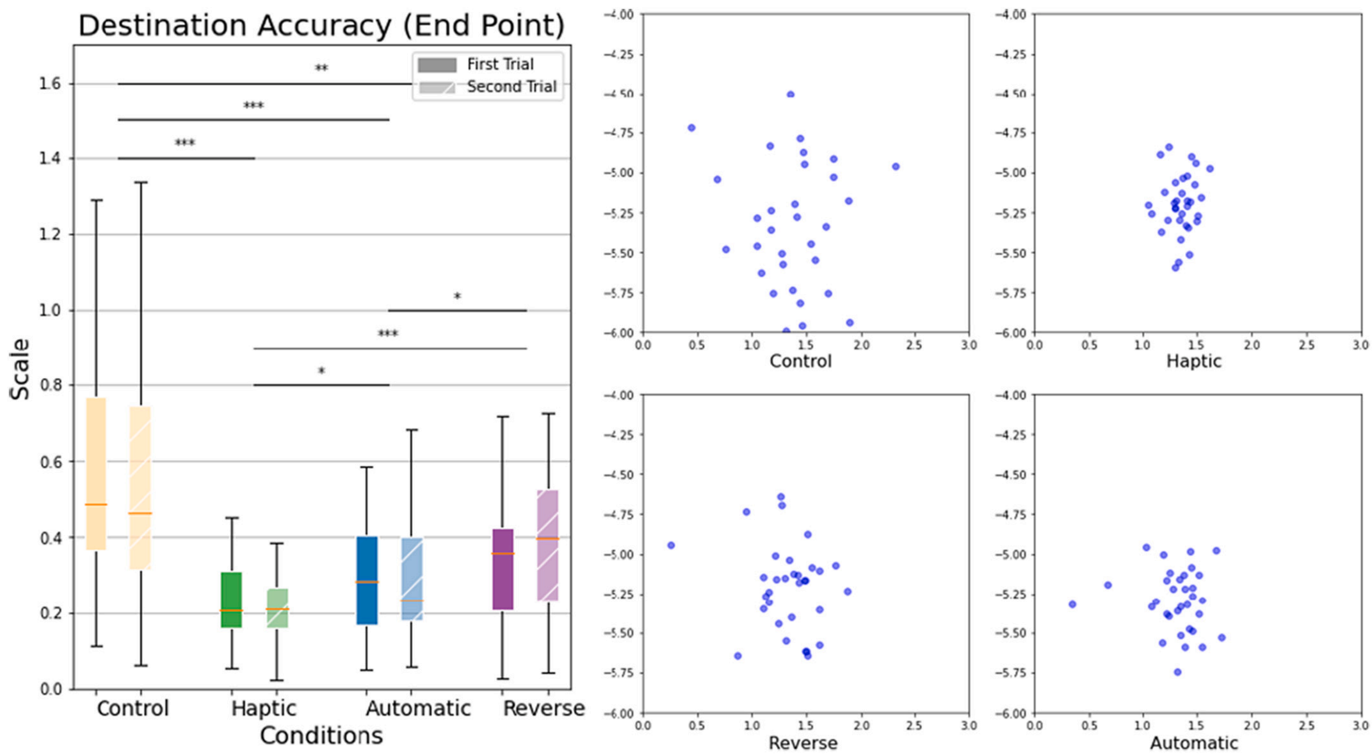

Fig. 17. Placing accuracy at End Point and the distribution from four conditions, * indicates statistically significant change (*$p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

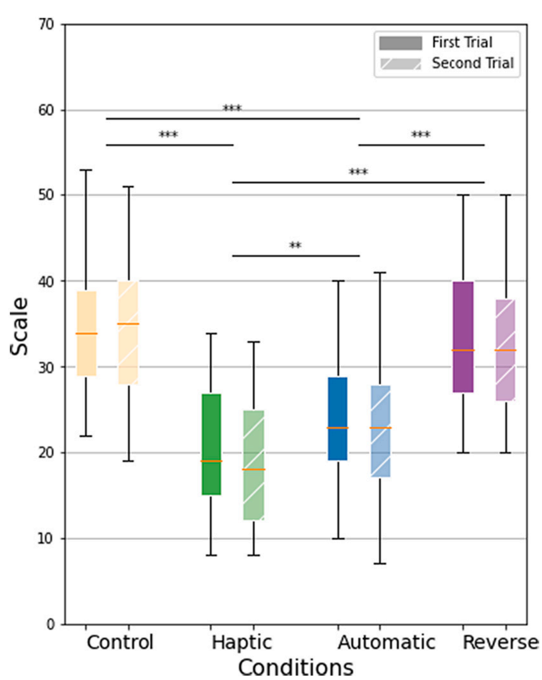

Fig. 18. NASA TLX comparison, * indicates statistically significant change (*$p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

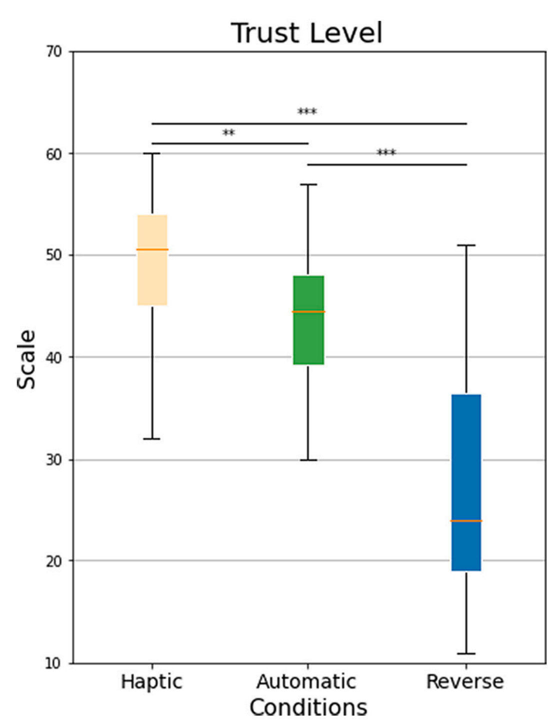

Fig. 19. Trust level comparison, * indicates statistically significant change (*$p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

6. Discussion

The findings of the human subject experiment indicated that the proposed haptics-based anti-sway control system could significantly improve the human operator's ability in anti-sway control and ultimately, the crane operation. Compared with the control condition when only a haptic-free joystick was used, both performance improvement and perceived benefits were observed for the haptic condition. As for the operation time, it showed that task completion time was significantly reduced under the haptic condition compared to the control condition ($p < 0.001$). As for the accuracy, participants under the haptic condition committed fewer errors in all metrics (collisions, trajectory, and placing, $p < 0.001$) compared to the control condition. In addition, the comparison within the human-in-the-loop control groups (Haptic and Reverse) further demonstrated the benefits of the haptic anti-sway control method. The Reverse (i.e., Push-button Pendant control) was designed to provide the same amount of freedom input and feedback as the Haptic method but with a different modality. Results showed that the Haptic system outperformed the Push-button methods in all accuracy metrics (collisions, trajectory, and placing, $p < 0.001$). This may be because of a more enhanced sensorimotor process via the proposed haptic control method. Because the system granted experiment participants an additional channel for sensing the kinematic states of the payload, as well as the dynamics of the mass center, perceived information was closely coupled with the actions taken. In addition, the haptic system also served as the controller for rebalancing the payload. In such a way, the feedback and control commanding processes were fully integrated. It helped the experiment participants leverage the haptic motor processes for a more timely and precise corrective motor action. In contrast, the commonly practiced control method, and the push-button pendant method, were not always beneficial, possibly due to the separated haptic motor processes between visual input and the push-down activation, or a delay that the pendant might not be activated in time. As a result, participants may have faced more challenges in handing over the control method compared to the haptic method, which was a more intuitive and natural method. This was supported by psychometric surveys. In the NASA TLX survey, participants reported significantly lower workload levels related to the Haptic condition compared to the Control condition ($p < 0.001$) or the Reverse condition ($P < 0.001$). In terms of Trust in Automation (TiA) evaluation, participants also reported higher trust levels with the Haptic condition than with the Reverse condition ($p < 0.001$).

In addition, it was found that a human-in-the-loop method via the haptic control system outperformed the automatic anti-sway suppression. The data showed that using the Haptic control system, participants tended to collide fewer poles in the ZigZag task compared to the Automatic control ($p = 0.001$). Interestingly, the overall anti-sway performance was similar between the two conditions in terms of the measurement of trajectory accuracy ($p = 0.169$). Therefore, we conjectured that the Haptic control system could help participants leverage better fine-tuned strategies during load positioning, especially when unexpected sway happened. In the Automatic condition, participants had to rely on the PID algorithm to adjust the sway angles and therefore might have to give up partial awareness in control, i.e., the loss of sense of ownership. The significantly higher End Point accuracy under the Haptic condition ($p = 0.015$) could also support this conjecture. Besides, the comparative advantages of a human-in-the-loop approach in comparison with the automatic approach based on the PID controller may be due to the difficulty of solving the optimal control problem with a high level of nonlinearity, as well as the loss of sense of ownership. In our test case, the crane trolly was connected with the hook using a soft tendon, and then the hook was connected with the payload with a hinge. It was a double pendulum system with additional unmodeled nonlinearities such as the deformation of the tendon. As such, solving the dampening signals for bringing the payload to the desired trajectory is extremely difficult if not impossible. In contrast, the balance maintaining task is considered nontrivial for healthy adults. The haptics-based force balance simulator provides an opportunity for human operators to utilize the natural ability of balance keeping.

7. Conclusions

Traditional methods for anti-sway controls rely on heavy training or experience of the human operator. Operating tactics, such as “wait and see”, minimum safe speed and “reverse plugging” (i.e., reverse the gear before reaching the target) [40], are used by experienced operators. In the past decades, literature has tested various automatic anti-sway suppression methods based on the classic control theory, using a calculated dampening signals to overcome and compensate for the deviations. The automatic approach for anti-sway controls is problematic in several ways that affect the viability. First, the computing cost for solving the solution for optimal control problems is high, and thus, most automatic anti-sway control methods only address single pendulum cranes, such as overhead cranes. Tower cranes, in contrast, present a more complex configuration that can only be modeled as a double pendulum problem. The additional locomotion functions of tower cranes, such as trolly moving on the job, and the self-rotation of the crane platform, add further nonlinearities to the model that can hardly be captured by a standard model for optimal control solutions. Second, the use of automatic controls breaks the natural loop of the human sensorimotor process that is critical for coordinating complex motor actions. Most automatic approaches ignore the importance of haptic motor process human operators use for corrective motor actions.

This study fills the gap of anti-sway control methods by proposing and testing a first-of-its-kind haptics-based force balance simulator for human-centric anti-sway controls in crane operations. It presents serval technical advantages in comparison with similar human-centric systems such as [13,82]. First, the existing haptic simulators for anti-sway control are focused on reproducing the kinematic states of the crane components, such as the hook and trolly. In contrast, our method can reproduce the positional and forces information of the payload directly. As a result, the feedback provided to the human operator is more accurate and straightforward for intuitive reactions. It is attributed to the recent development of the physics engine that can simulate soft body objects and nonlinear physical interactions. For example, in our system, the deformation of the tendon connecting the trolly and hook can be accurately reproduced, including the internal tension parameters. And the nonlinear interactions between the trolly and the tendon, and between the hook and the payload, can be modeled with the physics engine as well. All these modeling abilities enable the capture of the kinematic states of the payload connected to the tendon. Second, because of the ability to directly capture the states of the payload, our system adds an additional DOF to capture the balance of mass center of the payload via the haptic devices. We repurposed and connected two haptic controllers, forming a “seesaw” type of haptic simulation. While previous methods treat the payload as a single object without any shape. This additional dimension allows the human operator to correct the balance of the payload as well, especially when the payload is big in size and subject to loss of balance. Last, our study also provides direct evidence about how the augmented human-in-the-loop method outperforms the traditional methods and automatic anti-sway methods. Both the performance and human function benefits are documented for promoting the agreement on a human-centric approach for future complex material handling problems. Overall, this study has validated that the proposed haptic-based anti-sway control system had unique advantages in mitigating sway problems in tower crane operations. It has also provided a methodological workflow to test new anti-sway control systems for other crane models in various contexts. Our next step is to extend its applications in other crane models such as mobile cranes and luffing tower cranes with different mechanical dynamics models.

This study presents several limitations that should be addressed in the future. First, as a pure simulation study, empirical evidence will be needed with a real-world crane operation test. A key consideration of running a simulation study is the safety concerns. As mentioned earlier, we employed multiple strategies to ensure that our physics-based crane simulation closely matched the operational parameters and mechanical dynamics of real full-sized tower cranes, with physics behaviors generated by the physics engine. As a result, the simulation results from the study should have provided comparable results of human operator behaviors with real applications. After main safety and cost concerns are addressed, it will be our future agenda to test the proposed system with a real tower crane for validation purposes. At this point, the scope of this study is only to prove the concept, and to provide preliminary human-subject experiment data for the initial design. Second, new sensing methods are needed to collect high-fidelity data about the payload kinematic states. The proposed method relies on data directly showing the positional and force changes of the payload for the feedback and control. While most existing sensing systems are designed for tracking crane states instead of those of the payload. Sensors embedded in the payload, or remote sensing such as computer vision approaches, will be tested for collecting payload state data. As for collecting data from a real crane, our design will rely on two methods to obtain the position and acceleration of the payload object. First, vision-based methods such as computer vision will be utilized for dynamic position estimates. Multiple GRB cameras or other ranging sensors such as LiDAR will be deployed. For one design, one of the cameras can be mounted on the trolley with a facing down position to identify the position of the payload in the X and Z directions, while other cameras are mounted on the vertical column, facing to the payload, which can provide information about the position in X and Y directions. Combining both sources, complete positional data in a 3D space XYZ can be recovered. An inertial measurement unit (IMU) can be used to further correct the tracking errors from the cameras. Such a method has been tested in previous literature, such as [66]. The second method will be based on the estimate of the angle between the rope and the payload. We will install an IMU on the hook to detect its dynamic posture, in addition to the IMU installed on the payload. With the two IMU sensors, the roll, yaw, and pitch angles of the hook and payload can be calculated based on trigonometric functions. Similar approaches have been tested in [4,18]. Our next plan is to test these methods. Last, the existing crane mechanical designs should be renovated to enable direct control of the balance of the payload. Existing anti-sway controls rely on the dampening or velocity control of the trolly. While our approach proposes to exert external forces directly on the payload for rebalancing, a secondary mechanical structure that can connect the crane gears to the payload should be examined.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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