Human Workload Evaluation of Drone Swarm Formation Control using Virtual Reality Interface

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ABSTRACT

This paper presents experimental data that evaluates the human workload in interacting with a drone swarm using a virtual reality (VR) interface. Formation control algorithm integrated into the system aids a human operator in interacting with the drone swarm. VR head-mounted display (HMD) will help to visualize the swarm, enabling teleoperation control. The algorithm will maintain each drone's position in the formation, making it simple to operate several drones at once. An experiment scenario is proposed to assess the workload using a joystick and a VR controller by moving the drones through a VR HMD. According to the current findings, humans could achieve a smoother control with a VR controller compared to a joystick controller. However, a VR controller's average workload (62.67 ± 30.29) is still twice as high as a joystick controller's (29.67 ± 12.00) based on the NASA-TLX assessment.

CCS CONCEPTS

• Computer systems organization → Embedded and cyber-physical systems → Robotics → External interfaces for robotics

KEYWORDS

Formation Control; Virtual Reality; Swarm Robotics; NASA-TLX; Human–Robot Interactions; Human Workload Evaluation

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1 INTRODUCTION

One-human-multiple-robot collaboration takes an advantage of human decision-making skills to control the robotic swarm system. Collaboration between robotic swarm and human operator requires an interface to execute commands and receive feedback. For example, Hatanaka et al. [1] suggested controlling the robotic swarm through a tablet interface by using tapping and dragging motions on the tablet to control them to move to a desirable position or velocity. A 2-D display feedback interface is used to visualize two-dimensional movement, such as that of a ground robot swarm. However, it may be unsuitable for drone swarms which moves in a three-dimensional (3-D) coordinate.

According to St. John et al. [2], the advantage of 3-D visualization is the ability to visualize depth, object scaling, and shadows. Therefore, the drone swarm system in this experiment will be visualized with a three-dimension virtual reality (VR) HMD. Human operators could interact with the drone swarm through the command interface, joystick or VR controller.

In real applications, human operator may initially have no access to some drones or get disconnected from them mid-flight. Therefore, each drone is assigned a local formation control algorithm that considers the positions and velocities of the other drones in the swarm. The formation control would allow the control of multiple drones as if they were a single unit. Moreover, in this experiment, the drone swarm formation control was used in combination with control barrier function (CBF) [3], specified as a safe operating condition for the drones. The function maps the drone's state, such as its position and velocity, to ensure that its total state value is within a certain threshold (avoiding drone collision or drones moving out of their workspace).

By effectively combining drone swarm control through virtual reality, greater control of the swarm can be achieved, providing significant benefits to various real-world applications. For example, virtual reality HMD can visualize information from sensors as heat maps used to improve firefighters' efficiency [4]. Moreover, applying a multi-drone system in precision agriculture is another potential application that can be addressed [5]. In the effort to utilize VR to improve human-swarm interaction, several literatures reviewed by Dianatfar et al. [6] have also verified the effectiveness of virtual reality for human-robot collaboration. However, studies on how the VR interface would affect the human operator and how each type of command interface affect the workload of human operators are yet to be discussed extensively. Furthermore, consensus-based formation control has been extensively researched by Egerstedt et al., Lizzio et al., and Hatanaka et al. [7, 8, 9], from a theoretical perspective but has not been implemented much with real drone swarms, especially controlling through a VR interface.

This paper proposed an experimental demonstration of controlling a drone swarm which are visualized through virtual

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reality. Swarm operation is controlled through both a traditional joystick controller and a novel VR controller. The swarm formation control is integrated with real drones with the help of CBF. A proposed experiment scenario is assessed using NASA-TLX human workload analysis to see how well the VR controller interface performs when controlling the group of drones. Previous studies have also shown that NASA-TLX tools can be used to assess how VR can improve human-drone interaction [10, 11]. In this experiment, we will contrast the workload involved in interacting with a group of drones with a joystick versus a VR controller. Finally, based on the NASA-TLX observation, a potential future development will be discussed.

2 METHODOLOGY

2.1 System Overview

From Fig. 1, the position $(p_i, \dots, p_n)$ and orientation $(\theta_i, \dots, \theta_n)$ of all drones in the workspace are acquired from the motion capture system and sent to the central controller. The central controller consists of data functions ready to be directly request by any drone at any time. For example, the position of each drone, the average position of accessible drone, drones' state etc. The drone uses these data to perform formation control, which will be stated in the following subsection. Unity, a 3-D development platform, running on Windows cannot acquire these data directly from the central controller on the Robot Operating System (ROS) running on Ubuntu. Data publishing and subscribing between ROS and Unity require ROSBridge from the ROS side and ROS# from the Unity side. Viewing the created virtual environment requires SteamVR, a Unity plugin, to connect to the Oculus Rift S (HMD). In addition, SteamVR is used to acquire data from human operator input from either a joystick controller or a VR controller. The human inputs $(u_h, \dot{\theta}_h)$ are sent to Unity for publishing to the accessible drone indicated as yellow drones (Drone #1 and #2). The white drone (Drone #3), which the operator does not have control over, will automatically reposition itself based on the position of its neighbors.

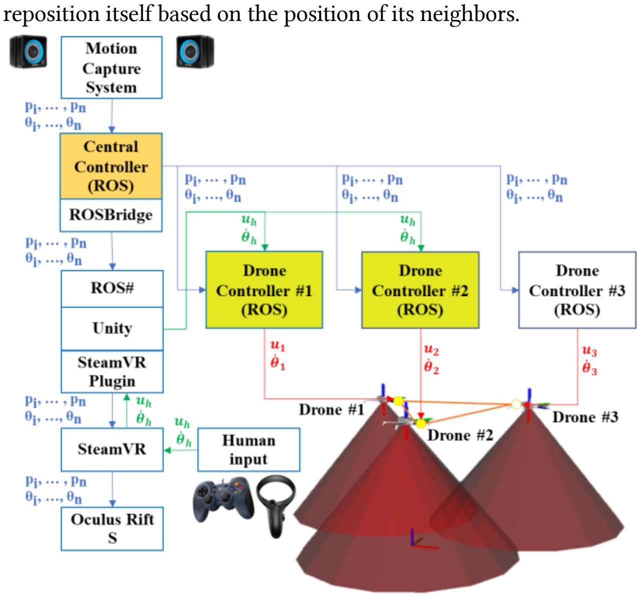

Figure 1: System diagram for drone swarm experiments

2.2 Formation Control

Formation control of both position and orientation, based on the PI-consensus control, can be achieved with these equations [9].

$$u_i = \sum_{j \in N_i} a_{ij}(q_j - q_i) + \sum_{j \in N_i} b_{ij}(\xi_i - \xi_j) + \delta_i u_h \quad (1.1)$$

$$\dot{\xi}_i = \sum_{j \in N_i} b_{ij}(q_j - q_i) \quad (1.2)$$

$$q_i = p_i + d_i \quad (2)$$

$$\dot{\theta}_i = \sum_{j \in N_i} c_{ij}(\theta_j - \theta_i) + \delta_i \dot{\theta}_h \quad (3)$$

In the above equation, u_h and $\dot{\theta}_h$ represent the linear and angular velocity from the human input. While p_i and θ_i refer to the position and orientation of drone- i relative to world axis respectively. Using equation (1), PI-consensus algorithm is implemented to achieve a common position for each drone. Then equation (2) is substituted into (1) to assign each drone into the assigned formation position with distance d_i. Fig. 2 shows that the system achieved a stable PI-consensus position control after 6 seconds for the x-coordinate when a step human input of 1 is applied for 4 seconds, resulting in $q_{x1} = q_{x2} = q_{x3}$. Fig. 3, represents the drone's position in the x-coordinate (p_{x1}, p_{x2}, p_{x3}) when applied with human operator input and formation control algorithm. For orientation control, controller (2), P-consensus is used so that all drone can always achieved common orientation which is important especially when there is a limited number of accessible robots. Without common orientation, it will be extremely difficult for human operator to input velocity commands.

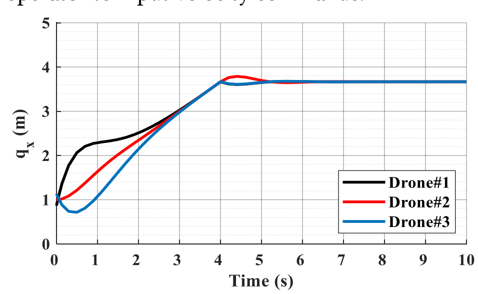

Figure 2: Time series data of x-coordinate (q_x) relative to world axis when applied with PI-consensus control

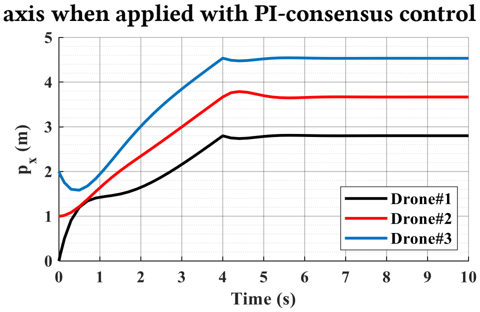

Figure 3: Time series data of x-coordinate (p_x) relative to world axis when applied with formation control

3 EXPERIMENTAL SCENARIOS

The joystick controller uses stick and button to control the position and orientation of the drones. For VR controller, "trigger button" is used to initialize VR controller pose. The linear velocity input is determined by moving the VR controller away from that reference position to a new x, y, z position. For orientation, rotating the VR controller to a new θ will result in an angular velocity input. Human operator have an input limit value of between [-1, 1] for linear velocity and angular velocity. Initially, three drones are placed in the workspace with random position and orientation. When the main program of this experiment is executed, the drones are designed to form a triangular formation.

The first and second experiment was done with joystick and VR controller respectively, human operator can visualize every drone inside the HMD. In these proof-of-concept experiments, the human operator will only be able to give direct input to the yellow accessible drones (Drone #1 and #2). While the white non-accessible drone (Drone #3), as shown in Fig. 1, will adjust its position based on the formation control algorithm. Experimental videos for these two experiments are shown in Supplementary Material [S1] and [S2] respectively.

In evaluating the human workload, the third and fourth experiments were conducted, similar to the previous experiments, but with an randomly assigned goal position that the human operator must move the swarm towards. Instead of visualizing every drone in the system, human operator visualize only the average position of accessible drone (shown as a green drone). A random pose (r_p) is generated as a goal pose shown as a red drone. The new poses are generated every 20 seconds. Human operator navigates the green drone toward the red drone's position. Fig. 4 shows the third experiment where the human operator uses a joystick to control the swarm to a random pose. Fig. 5 shows the fourth experiment with human operator using a VR controller to control the swarm to a random pose. See full operation video during data collection with joystick controller and VR controller from Supplementary Material [S3] and [S4] respectively.

Figure 4: Controlling swarm to a randomly generated pose (r_p) with joystick controller

Figure 5: Controlling swarm to a randomly generated pose (r_p) with VR controller

The log data from the third and fourth experiments are used to assess the control capablilities between joystick controller and VR controller after the experiment. Additionally, a small group of participants (n = 5) was requested to test the experiment and provide feedback using the NASA-TLX questionnaire. These participants were chosen from individuals who had never used the system before. Prior to the experiment, participants would practice using the joystick controller and the VR controller, followed by a 5-minute real test by using each controller. After each experiment, the individual was given the questionnaire to complete in order to compare the two results.

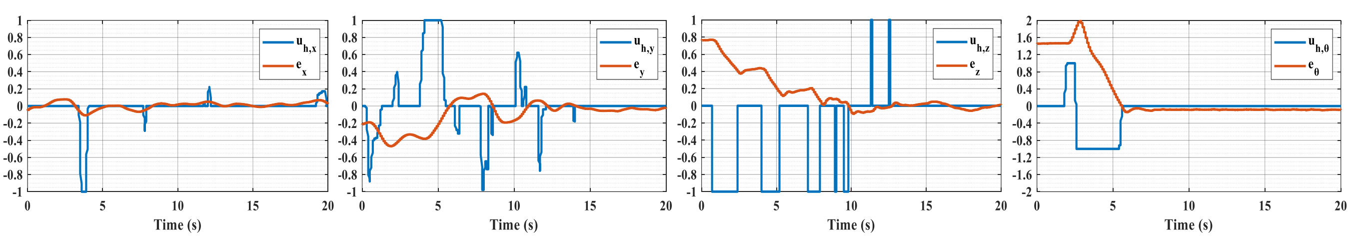

Figure 6: Time series data of human input(u_h) and pose error (e) of joystick controller.

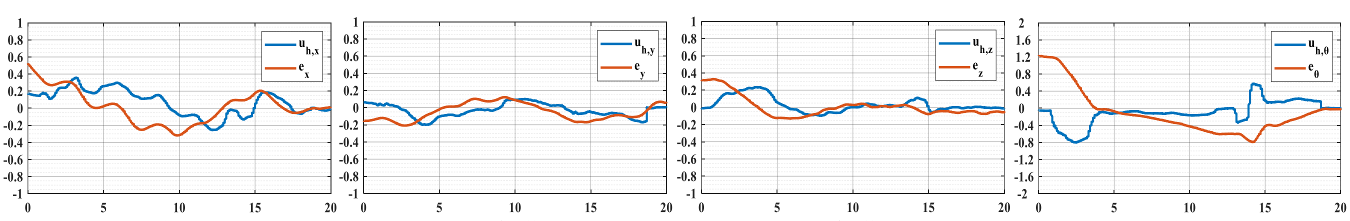

Figure 7: Time series data of human input(u_h) and pose error (e) of VR controller.

4 EXPERIMENTAL RESULTS

4.1 Human operator control capabilities

The log data from the third and fourth experimental demonstrations were gathered and plotted individually in the x, y, z, and θ coordinates. The graphs show a time series data format displayed with human input (u_h) and pose error ($e = r_p - y_h$) for a single duration of a randomly generated pose. As can be observed from Fig. 6, the results of the experiment using the joystick controller, a human operator often sends input with an extreme action of either -1 or 1 command value. Additionally, when the button input is used, the human operator can only input values of 1 or -1 for the z-coordinate control (altitude control). As a result, the position of the drone generally changes quite abruptly.

While in Fig. 7, which displays the experiment's outcomes using the VR controller, the human operator typically provides a smoother control input due to the nature of the VR controller. The interface for a VR controller, however, gets to the random point slower than a joystick controller. The reason is that it is more difficult to move the arm with a VR controller to input velocity in one axis without also affecting the velocity of other axes. It is more difficult to give input control in only one axis since the human arm revolves (in a circular motion) around the shoulder.

4.2 Human Workload Assessment: NASA-TLX

Table 1: Controller comparison (Weighted Score)

	VR controller (mean ± SD) n = 5	Joystick controller (mean ± SD) n = 5
Mental Demand	279.00 ± 148.26	140.00 ± 97.79
Physical Demand	62.00 ± 81.67	6.00 ± 13.42
Temporal Demand	82.00 ± 91.96	114.00 ± 69.14
Performance	164.00 ± 149.81	78.00 ± 35.11
Effort	161.00 ± 76.84	83.00 ± 87.44
Frustration Level	192.00 ± 199.67	24.00 ± 24.08

According to the preliminary NASA-TLX observation, shown in Table 1, the average workload of a VR controller (62.67 $\pm$ 30.29) is about twice as high as a joystick controller (29.67 $\pm$ 12.00). Despite the movement-intuitiveness potential, the observation shows that the current VR interface has some issues that need to be improved upon to interact more effectively with the swarm of drones.

One of the key issues identified in this qualitative assessment interview is the VR controller's difficulty in remaining steady, especially once it has reached the goal's position. In a joystick interface, a human operator just needs to release their fingers from the joystick to stop the drone swarm action. The VR controller, however, is unable to do so instantly. The VR controller must be returned to the initial reference point and kept there by a human operator. Thus, it poses greater mental demand and effort from the human operator.

The interdependency between each axis in this scenario also poses a challenge for the VR controller, making it difficult to change the position of one axis without altering the position of the other axis. These factors may also explain why using a VR controller is more physically demanding and frustrating than using a joystick controller since a human operator must physically move the VR controller while appropriately adjusting its position and orientation to prevent axis intertwining.

5 DISCUSSION AND FUTURE WORKS

We believe that VR interface offers significant benefits for enhancing human-robot swarm interaction in the remote operation application. Compared to the joystick controller, VR controller has numerous advantages such as more intuitive, smooth, and flexible interaction with the swarm of drones. However, based on the early NASA-TLX observation in this experiment, some potential improvements may need to be implemented to make the VR controller less mentally and physically demanding.

As shown in Fig. 8, virtual displays showing the initial reference point of the VR controller might be added to help the human operator return to its initial position, keeping drones stationary. Furthermore, adjusting the gain of VR controller and possibly even adding a dead zone around the initial reference point could help keeping a steady motion which will lessen the mental demand factor. On the other hand, in improving the axis interdependency issue, a virtual guidance line might also be included as a suggestion for the human operator to move the VR controller in a more efficient way.

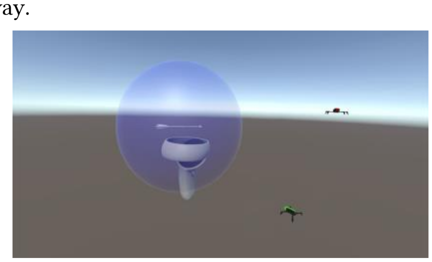

Figure 8: Reference point display and guideline in VR

6 CONCLUSION

In this research, we present a preliminary observation on how a VR interface is being used to interact and control a group of drones. We implemented formation control using three drones. Then, we compared log and NASA-TLX analysis for interacting with group of drones using a joystick and a VR controller. According to the results of this preliminary investigation, the VR controller offers advantages in making the control of drone swarms smoother and more flexible. However, for the proposed experiment scenario, the average workload of the VR controller (62.67 $\pm$ 30.29) is roughly twice as high as that of the joystick controller (29.67 $\pm$ 12.00). Finally, we discuss potential improvement that could be made to reduce the task load using VR controller for future implementation. The introduction of visual guides such as initial position reference and optimal arm movement suggestion, along with a designated dead zone may prove useful in subsequent research and experiment.

REFERENCES

[1] Hatanaka, T., et al., A Passivity-Based System Design of Semi-Autonomous Cooperative Robotic Swarm. *Mechanical Engineering*, 2017. 139(06): p. S14-S18.

[2] St. John, M., et al., The use of 2D and 3D displays for shape-understanding versus relative-position tasks. *Human Factors*, 2001. 43(1): p. 79-98.

[3] Ames, A.D., et al. *Control barrier functions: Theory and applications*. in 2019 18th European control conference (ECC). 2019. IEEE.

[4] Roldán-Gómez, J. J., et al. (2021). "A survey on robotic technologies for forest firefighting: Applying drone swarms to improve firefighters' efficiency and safety." *Applied Sciences* 11(1): 363.

[5] Skobelev, P., et al. *Designing multi-agent swarm of uav for precise agriculture*. International Conference on Practical Applications of Agents and Multi-Agent Systems. 2018. Springer.

[6] Dianatfar, M., J. Latokartano, and M. Lanz, Review on existing VR/AR solutions in human–robot collaboration. *Procedia CIRP*, 2021. 97: p. 407-411.

[7] Egerstedt, M., et al., Interacting with Networks of Mobile Agents, in *Large-Scale Networks in Engineering and Life Sciences*, P. Benner, et al., Editors. 2014, Springer International Publishing: Cham. p. 199-224.

[8] Lizzio, F.F., E. Capello, and G. Guglieri, A Review of Consensus-based Multi-agent UAV Implementations. *Journal of Intelligent & Robotic Systems*, 2022. 106(2): p. 1-10.

[9] Hatanaka, T., et al., A Passivity-Based Approach to Human–Swarm Collaboration and Passivity Analysis of Human Operators, in Trends in Control and Decision-Making for Human–Robot Collaboration Systems, Y. Wang and F. Zhang, Editors. 2017, Springer International Publishing: Cham. p. 325-355.

[10] Cauchard, Jessica R., et al. "Drone. io: A gestural and visual interface for human-drone interaction." 2019 *14th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*. IEEE, 2019.

[11] Albeaino, Gilles, et al. "DroneSim: A VR-based flight training simulator for drone-mediated building inspections." *Construction Innovation* (2021).