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Effects of Haptic and 3D Audio Feedback on Pilot Performance and Workload for Quadrotor UAVs in Indoor Environments

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Effects of Haptic and 3D Audio Feedback on Operator Performance and Workload for Quadrotor UAVs in Indoor Environments

Robert M. Philbrick

A thesis submitted to the faculty of Brigham Young University in partial fulfillment of the requirements for the degree of Master of Science

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ABSTRACT

Effects of Haptic and 3D Audio Feedback on Operator Performance and Workload for Quadrotor UAVs in Indoor Environments

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Master of Science

Indoor flight of unmanned aerial vehicles (UAVs) has many applications in environments in which it is undesirable or dangerous for humans to be, such as military reconnaissance or searching for trapped victims in a collapsed building. However, limited visual feedback makes it difficult to pilot UAVs in cluttered and enclosed spaces. Haptic feedback combined with visual feedback has shown to reduce the number of collisions of UAVs in indoor environments; however, it has increased the mental workload of the operator. This thesis investigates the potential of combining novel haptic and 3D audio feedback to provide additional information to operators of UAVs in order to improve performance and reduce workload.

Many haptic feedback algorithms, such as Time to Impact (TTI) [1], have been developed to help pilot UAVs. This thesis compares TTI with two new haptic feedback algorithms: Omni-Directional Dynamics Springs (ODDS) and Velocity Scaled Omni-Directional Dynamic Springs (VSODDS). These novel algorithms are based on the idea that dynamic springs are attached to the haptic controller in all directions. This thesis is unique by augmenting visual and haptic feedback with real-time 3D audio feedback. Continuous Directional Graded Threshold (CDGT) and Discrete Directional Graded Threshold (DDGT) are two novel algorithms that were developed to provide 3D audio warning cues to operators. To reduce sensory overload, these algorithms play a graded audio alert cue in the direction of velocity and when within a threshold distance of an obstacle. In order to measure operator workload, many researchers have used subjective measures, which suffer from subject bias, preconceptions, and ordering. Instead of using a subjective measure, experimental data is used to objectively measure operator workload using behavioral entropy, which works on the idea that humans work to reduce entropy by skilled behavior [2].

QuadSim, a robust and versatile indoor quadrotor simulator, was developed as a test bed for visual, haptic, and 3D audio feedback. Using QuadSim, a human subject experiment was performed to determine the effectiveness of haptic and 3D audio feedback on operator performance and workload. The results of the study indicate that haptic feedback significantly reduced the number of collisions and collision length. Operator workload was decreased in the side-to-side direction by VSODDS but was adversely increased by TTI. Overall, VSODDS outperformed the other haptic algorithms. Unlike haptic feedback, audio feedback proved to be neither helpful nor harmful in improving performance or reducing workload.

Keywords: unmanned aerial vehicles, haptics, force feedback, 3D audio, multimodal interaction, behavioral entropy
I could not have completed this thesis nor my masters degree without the help and support of so many people. I am grateful for the help provided and the patience shown by family, friends, professors, and colleagues.

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CHAPTER 1. INTRODUCTION

The ability to pilot small unmanned aerial vehicles (UAV) in indoor environments is of great interest in many fields including military reconnaissance, searching for trapped victims in damaged buildings, locating chemical leaks in a plant, or other situations that result in danger, discomfort, or inconvenience to humans. The hover and omni-directional flight capabilities of a quadrotor UAV (Figure 1.1) make it ideal for navigating through indoor environments that contain obstacles. However, these flight characteristics can also increase the number of collisions and mental workload of the operator due to lack of visual perception in all directions.

Haptic feedback has been explored as one method for providing additional information to operators of UAVs in order to prevent collisions. Feedback forces calculated from the quadrotor’s position and velocity relative to an obstacle can be applied to the operator’s hand as a way to provide spatial-tactile warning cues of potential collisions in any direction. Research has shown that combining haptic force feedback with visual feedback can reduce the number of collisions of a remotely operated small UAV in indoor environments [3–5].

Although haptic force feedback has been shown to reduce the number of collisions, it has not been shown to decrease the mental workload of the operator, and, in some cases, has been shown to increase it [4, 5]. Research suggests that multimodal feedback, specifically 3D audio combined with haptic feedback and a visual interface, can increase situational awareness and reduce workload in a variety of applications [6].

The objective of this research is to improve and explore other sensory modalities as means of providing additional information about the indoor environment to operators of UAVs. In particular, this research focuses on augmenting visual feedback by also providing haptic force feedback and 3D audio alert cues. The effectiveness of this multimodal approach is determined experimentally by analyzing how the additional sensory modalities affect collision avoidance, the operator’s workload, and other measures.
1.1 Background/Related Work

Considerable research has been performed on haptic and audio feedback. This section provides further background to enrich the motivation behind this research. In particular, it presents related work to show how this research compares with what has been done by others in the areas of quadrotors, indoor flight, haptic and 3D audio feedback, and measurement of operator workload.

1.1.1 Quadrotors

Quadrotors, or quadrocopters, are small unmanned aircraft with four rotors that are symmetrically spaced about a central hub which houses the battery, autopilot, and other sensors and hardware (Figure 1.1). Often quadrotors are equipped with a camera to provide visual feedback to the operator. Quadrotors have the ability to hover and fly in any direction. The omni-directional flight capabilities of quadrotors allow them to make fast and sharp turns. The hover and highly acrobatic abilities make quadrotors ideal for use in indoor applications such as maintaining posi-
tion while monitoring an indoor environment [7] or avoiding debris while searching for victims in a collapsed building after an earthquake [8]. Fixed-wing aircraft are less ideal for use in indoor environments due to the fact that they must maintain a velocity in a forward direction to stay aloft and thus they are unable to hover or fly in any direction.

Unmanned ground vehicles (UGV) are often also used to explore indoor environments [9] or even provide indoor security surveillance [10, 11]. However, the presence of debris, stairs, furniture, or other obstacles may reduce the effectiveness of UGVs. Quadrotors, on the other hand, are able to avoid and navigate more efficiently around such obstacles. For the purposes of this research, quadrotors have been chosen over other rotorcraft such as helicopters, due to their simpler design, dynamics, and control implementation.

1.1.2 Indoor Flight

The use of UAVs is increasing in both military and civilian circles due to their wide range of applications and ability to keep humans out of danger. In the past the use of UAVs has been focused on outdoor applications due to size and energy constraints; however, with rise of micro technology and better, smaller batteries, UAVs have become smaller and more suited for indoor applications such as inspection and surveillance tasks. Some of these tasks could include searching for heat loss in conduits, or inspecting piping and pressure vessels for damage [12]. Significant effort has also been made in improving controllers for UAVs that provide nearly full autonomous flight and navigation [13–16]. However, many inspection, search and rescue, surveillance, and military tasks require high-level reasoning that can not easily be automated. For instance, a reconnaissance mission might require a human operator to identify a target before further action is taken. Since most human inspectors are not trained in piloting aerial vehicles and indoor flight is challenging for even trained operators, it is important to develop methods to aid in the teleoperation of UAVs while permitting the operator to perform other tasks. The multimodal feedback method investigated in this research has the possibility of providing experienced and inexperienced human operators with extra information about the indoor environment to assist in teleoperation and/or reduce operator training time.

Even though a quadrotor’s omni-directional flight ability is desired for indoor flight, it increases the potential for collisions, especially in directions of no visual feedback. A couple
solutions to this problem are to add additional cameras or to gimbal the camera. Both of these ideas would add additional weight to the quadrotor which would require a more expensive and larger rotor craft to carry the additional payload. Also, extra cameras would require the operator to monitor multiple screens which would greatly increase the difficulty of the task. Additional video streams also requires greater data bandwidth and more complicated hardware. A gimbaled camera would also add to the complexity by requiring the operator to both control the quadrotor and the gimbal. Using video feedback itself, regardless of how many cameras or camera sophistication, has drawbacks in teleoperation due to loss of sensory perception by viewing a 3D world on a 2D screen. Piloting a UAV using a remote camera video feed is like “looking at the world through a soda straw” [17].

1.1.3 Haptic Feedback

To counter the loss of visual perception, many researchers have proposed augmenting visual feedback by adding a new sensory perception, the sense of touch. This haptic feedback approach provides the operator extra information about the environment by exerting forces on his or her hand or other parts of the body. This approach is advantageous because it only requires the operator to focus on one fixed camera display while simultaneously receiving haptic cues.

Haptic feedback has been researched as a sensory method for providing flight information to pilots of manned air vehicles. Some of this research includes providing tactile cues on the aircraft control stick to convey information displayed on the flight director [18] or to help the pilot maintain an appropriate vertical trajectory [19]. Tactile torso displays have also been researched as a countermeasure to spatial disorientation sometimes felt by pilots [20].

Haptic feedback has also been used to assist in the teleoperation of UGVs [21–23] and UAVs. In 2004, Boschloo et al. [24] presented four collision avoidance systems using haptic feedback to remotely operate a helicopter. The haptic feedback force for each system is calculated using artificial risk fields which provide an indication about the risk of colliding with an obstacle. Each obstacle in the environment has a risk vector which acts as an artificial force on the UAV. All of the risk vectors are combined together to form an avoidance vector that is proportional to the feedback force felt by the operator. The four collision avoidance systems stem from two types of risk fields, basic and parameterized risk fields, and the direction of the risk vector, radial or
normal. The parameterized risk field is an adaptation of the basic risk field that adds parameters to better define the shape of the field and thus alter how the operator perceives and reacts to the risk field. In a 2D simulation, they found that the parameterized risk field employing radial risk vectors performed the best in collision avoidance.

To increase the perception of a remote environment to the operator of one or even multiple UAVs, Son et al. [25] developed a framework to provide haptic feedback cues to the operator. They investigated using the UAVs’ velocity, proximity to obstacles, and a combination of the two to create haptic cues. The velocity method was created to transmit a strong haptic cue when the UAVs are maneuvered towards an obstacle; whereas, the distance to obstacles method generates a repulsive force based on an artificial potential function. In a psychophysical experiment, they determined that an operator of UAVs is better able to sense the remote environment using a haptic cue based on the velocity information of the UAVs.

Researchers have hypothesized that haptic force feedback would decrease operator workload in addition to reducing the number of collisions while piloting a UAV remotely [4, 5]. However, in examining the effects of haptic feedback in assisting an operator to guide a UAV helicopter along a 2D trajectory down the middle of a virtual tunnel, Lam et al. showed that haptic feedback did provide better path-following performance and thus fewer collisions, but the two haptic feedback methods employed yielded higher workload compared to no force feedback [4]. In another experiment using the same haptic feedback methods to control a UAV helicopter in navigating around obstacles, it was again discovered that haptic feedback significantly reduced the number of collisions but adversely increased the workload [5]. Considering that improved algorithms could be created to reduce collisions and workload, Brandt [3] developed new algorithms for calculating the force felt in haptic feedback. In the experiment, human subjects piloted a simulated quadrotor through a virtual 3D obstacle course using five candidate haptic force feedback algorithms. The results of his study indicate that haptic feedback vs. no feedback did reduce the number of collisions but did not always decrease the workload.

1.1.4 3D Audio Feedback

Another way to improve a quadrotor operator’s perception of a remote environment is to provide spatial, 3D audio alert cues. Just like haptic feedback, augmenting visual feedback with
another sensory modality such as the sense of hearing, can provide additional information about
the environment to the operator. However, unlike haptic feedback, very little research has been
performed in studying the effects of audio feedback in aiding the real time control of UAVs. The
research in this area has been more focused on providing warning cues to drivers of motor vehi-
cles [26], aiding in target acquisition [27,28] or to help monitor gauges, warning messages, and
other system data spread across multiple screens of a UAV or UGV ground control station [29,30].

In 2010, Maza et al. [29] examined different multimodal technologies to aid in the design
and development of ground control stations for UAVs. They designed several experiments em-
ploying different modalities to emulate an operator responding to an alert message displayed on a
screen of a ground control station. The task of the subject in each experiment was to, as quickly
as possible, press only buttons labeled as “Yes” that appeared on various locations across three
touch screens. In one of the experiments that used an aural modality, they displayed to the subject
wearing headphones a 3D audio cue in the same direction as the location of button. They found
that the response time selecting the button was quicker than compared without 3D audio. It was
also observed that the subject pointed their head directly to the correct screen upon immediately
hearing the audio alert cue.

Also investigating the effects of employing different sensory modalities, Gunn et al. [27]
performed an experiment to determine if supplementary cuing would enhance UAV operators’
performance in target acquisition. In this study, the participants were tasked to monitor a video
display terminal for a warning signal indicating the presence of an enemy target in the nearby
area. Once a warning was detected, the participant was required to locate and lock onto the target.
Additional visual, haptic, and aural cuing were provided in separate trials with the intent to reduce
the target acquisition time. The aural cue consisted of broadband noise pulses that were spatially
located in the same direction and position of the visual target. It was observed that the speed in
which participants acquired threats was faster with spatial audio cuing than with no supplemental
cuing.

1.1.5 Multimodal Feedback

Other research indicates that multimodal feedback can increase situational awareness and
reduce workload in certain applications [6]. Yu [31] experimented with using haptic, audio, and
multimodal feedback to assist blind people in reading and understanding digitized, scientific charts and graphs. The results indicate that multimodal feedback reduced workload when compared to haptic feedback alone. Haas [32] explored the use of tactile and 3D audio displays to enhance soldier performance in human-robot interaction tasks while in a moving vehicle. The results indicate that combined tactile and audio displays had a significantly lower workload than tactile and audio displays used separately. In exploring the design of a multimodal human-machine interface for teleoperation, Chou [33] showed that a multimodal interface can facilitate teleoperation and reduce the operator’s workload.

1.1.6 Workload

For the purposes of this thesis, workload is defined as the task demands on human operators while interacting with robots or machines [34]. The demands of the tasks can be physical, mental, and emotional. In general, human performance of a task often decreases as the workload imposed by the task or other factors increases. Since one of the main premises of this research is to determine if multimodal feedback reduces operator workload, it is critical to have a good method for measuring workload. Some of the most well-known methods for quantitatively measuring human workload are the dual task method, the measurement of physiological signals and a subjective evaluation method [35].

The dual task method involves performing two tasks simultaneously, the task of interest and a task that can more easily be measured. How well the latter task is performed is used as a measure of the workload [35]. An example of this is having a subject perform simple arithmetic such as adding and subtracting two-digit numbers while performing the task of interest. A concern with the dual task approach is that itself imposes a workload. This is a problem if fine sensitivity is required because it can be difficult to distinguish between small differences due to the imposed workload of the second task from those of the main task of interest.

Instead of adding a secondary task, it is possible to quantify workload by the measurement of a physiological phenomenon. For instance, in some cases an increased pulse rate could indicate an increase in workload. Some of the typical physiological effects used to measure workload are eye movement, brain waves, heart rate, skin conductance, respiratory rate, skin temperature, and others. For an example of using physiological signals to measure differences in cognitive loading
in haptic human-robot interactions see [36]. A problem with this approach is that it often requires special equipment to measure the physiological signal. Also, analyzing the data and correctly attributing the changes in the measure to changes in the workload of the task can be difficult and time consuming. It might also take multiple measurements of different physiological signals to accurately distinguish between workload levels, as found in [36].

A method that does not require a secondary task or special equipment is the subjective evaluation method. With this method, after completion of a task, subjects rate the degree of difficulty of a the task using a multi-point scale. The NASA TLX index is one of the most common subjective evaluation tools. The NASA TLX uses a weighted average of six sub scales to calculate a workload index [37]. This type of method is popular due to its ease of implementation. However, all subjective evaluation methods suffer from the fact that they are subjective. If a subject has a preconceived idea of the difficulty of a task then the rating they give will be biased. Also, subjective evaluations are often post hoc evaluations and are not able to accurately measure changes in workload throughout a task or in real-time.

Considering the limitations of the previously discussed methods, an alternative approach that does not impose a workload, require special equipment, and is objective instead of subjective was sought out. Such a method is behavioral entropy, which works on the idea that humans work to reduce entropy by skilled behavior [2]. A model is created to describe the desired or baseline behavior and the error between the model and the actual behavior is used to estimate the behavioral entropy. Higher entropy indicates there is greater deviation in behavior than predicted and thus a higher workload. Behavioral entropy is an unobtrusive, objective measure that can be calculated on or offline. Due to these desirable characteristics, behavioral entropy has been chosen as the method for calculating workload in this research. Details of this method will be described in Chapter 3.

1.2 Contributions

This thesis is able to add to work previously done with the following contributions:

- **Two novel haptic feedback algorithms.** These algorithms are specifically designed for three dimensional space and to improve upon what has been done before, particularly in helping reduce operator workload.
• **Implementation of real-time 3D audio feedback.** Very little to no work has been done with using 3D audio cues to help operators of UAVs avoid collisions. This thesis introduces two novel 3D audio feedback algorithms that provides real-time warning cues to UAV operators.

• **Improved simulation test bed.** A robust and versatile indoor quadrotor simulator has been developed. The simulator is able to display visual, haptic, and 3D audio feedback in three dimensions. Also, the simulator is extendable beyond the scope of this thesis because new indoor environments, feedback algorithms, settings, and experiments can easily be designed and implemented.

• **Implementation of behavioral entropy, an objective workload measure.** Most previous work relied on using subjective measures for calculating operator workload. This thesis demonstrates how behavioral entropy can be used in the context of UAV teleoperation to calculate an objective measure of workload.

1.3 Thesis Overview

The remainder of this thesis will be organized as follows:

• Chapter 2, *Haptic and 3D Audio Feedback Algorithms*, provides an overview and derivation of the different haptic and 3D audio feedback algorithms.

• Chapter 3, *Behavioral Entropy*, gives further background and explains how behavioral entropy is implemented in this research.

• Chapter 4, *Simulation System and Interface*, explains the features and development of Quad-Sim, the simulator created for testing the effectiveness of the multimodal feedback.

• Chapter 5, *Human Subject Experiment*, presents the design and implementation of a user study.

• Chapter 6, *Results and Discussion*, reviews and discusses the analysis of the statistical results of the human subject experiment.

• Chapter 7, *Conclusion*, provides concluding remarks and highlights future work and areas of improvement.
CHAPTER 2. HAPTIC AND 3D AUDIO FEEDBACK ALGORITHMS

This chapter provides the theory and mathematics behind the haptic force feedback and 3D audio feedback algorithms used in this research. First, three haptic feedback algorithms are considered:

- Time to Impact
- Omni-Directional Dynamic Springs
- Velocity Scaled Omni-Directional Dynamic Springs

Second, two novel 3D audio feedback algorithms are presented:

- Continuous Directional Graded Threshold
- Discrete Directional Graded Threshold

2.1 Haptic Feedback Algorithms

This section presents Time to Impact (TTI), Omni-Directional Dynamic Springs (ODDS), and Velocity Scaled Omni-Directional Dynamic Springs (VSODDS). TTI is a more traditional force feedback algorithm, whereas ODDS and VSODDS are novel pseudo-stiffness feedback algorithms, meaning the force displayed imitates a change in stiffness of the haptic controller.

2.1.1 Time To Impact

The Time to Impact (TTI) algorithm is based on work done by Balas [38] and Brandt [3]. It was chosen for this research because in a previous user study, it outperformed the four other algorithms developed by Brandt [1]. TTI uses the idea that as the time it would take for a UAV to
collide with an obstacle decreases, the haptic force increases to warn the operator of an increased chance of collision. The TTI is calculated using

$$TTI = \frac{d}{v}, \quad (2.1)$$

where \(d\) is the distance from the UAV to the obstacle and \(v\) is the velocity of the UAV in the direction of the obstacle. The feedback force is calculated using

$$F = \frac{k}{TTI} = \frac{kv}{d}, \quad (2.2)$$

where \(k\) is a tunable parameter to scale the feedback forces. Thus, as the velocity towards an obstacle and/or as the distance from an obstacle decreases, the force displayed to the operator increases as shown in Figure 2.1.

![Figure 2.1: TTI force output as a function of velocity and distance to an obstacle [1].](image)

Not only does the increased force provide a warning about a potential collision, it also directs the operator’s hand in the opposite direction, helping the operator avoid the collision. Since
the feedback force approaches infinity as the distance towards an obstacle approaches zero, the force is saturated to the maximum force that can be displayed by the haptic device.

A drawback of TTI is that in enclosed spaces the feedback force can go unstable and cause the UAV to oscillate. This is caused by the obstacle avoidance forces moving the position of the haptic end effector and thus moving the UAV in the opposite direction, potentially towards another obstacle such as the opposite wall in a tight hallway. In an attempt to mitigate this problem, Brandt added another dependency to TTI: the position of the input device. With input device position dependency added, the TTI force becomes:

\[
F = \frac{F_{\text{max}}}{2R} \left( p - R \frac{k_v}{d} \right),
\]

where \( R \) is the radius of the haptic device’s workspace area and \( p \) is the displacement of the haptic device. According to Brandt, “this is analogous to having a spring connected to the input device with the zero position of the spring changing according to the output from the force feedback algorithm. It rewards the user for doing the correct action [1].” In theory this seems to be the case but in practice TTI with input device dependency still suffers from oscillations in areas where obstacles are close together.

### 2.1.2 Omni-Directional Dynamic Spring

Omni-Directional Dynamic Spring (ODDS) is inspired by Brandt’s Virtual Spring algorithm [1] and Lam et al.’s work on stiffness feedback [39]. It uses the idea that the haptic device’s end effector is held in its zero position by virtual springs attached in all directions around the device. Thus, if the end effector is displaced, the user feels a spring force attempting to return the end effector to its zero position. The 3D force displayed by the haptic device is calculated using

\[
f = -Kx,
\]

where \( x = [x, y, z]^T \) is the 3D displacement of the haptic device and the matrix \( K \) dynamically changes the stiffness of the imaginary spring attached in the direction of displacement.
The matrix $\mathbf{K}$ is given by

$$
\mathbf{K} = \begin{bmatrix}
    k(d_x) & 0 & 0 \\
    0 & k(d_y) & 0 \\
    0 & 0 & k(d_z)
\end{bmatrix},
$$

and $k(d_i)$ is given by

$$
k(d_i) = \frac{d_{\text{max}_i} - d_i}{d_{\text{max}_i}} k_{\text{max}_i}, \text{ for } i = x, y, z.
$$

$d_{\text{max}_i}$ is the maximum desired or possible distance to an obstacle, $d_i$ is the distance to an obstacle in the $x$, $y$, or $z$ directions, and $k_{\text{max}_i}$ is a tunable parameter given by

$$
k_{\text{max}_i} = \frac{f_{\text{max}_i}}{\alpha_i x_{\text{max}_i}}, 0 < \alpha_i \leq 1, \text{ for } i = x, y, z.
$$

$f_{\text{max}_i}$ is the maximum allowable force that the haptic device can display and $x_{\text{max}_i}$ is the maximum allowable distance that the haptic device’s end effector can be displaced in the $x$, $y$, and $z$ directions. The parameter $\alpha_i$ is used to tune the maximum stiffness. The output force with respect to haptic $x$-direction displacement and distance to an obstacle is shown in Figure 2.2.

![Force vs. Haptic Displacement and Distance for ODDS](image)

**Figure 2.2:** ODDS force output as a function of haptic displacement and distance to an obstacle with $F_{\text{max}} = 6 \text{ N}$, $d_{\text{max}} = 10 \text{ m}$, and $\alpha = 0.3$
ODDS, a stiffness algorithm, differs from force feedback algorithms, such as TTI, because the algorithm itself does not cause the haptic device’s end effector to overshoot its zero position. This may be beneficial by providing more stable control, whereas force feedback algorithms can cause operators to counteract the overshooting motion caused by the force feedback, particularly in situations where obstacles are very close to each other [39]. Another potential benefit of ODDS is that it may allow the operator, with small test deflections, to feel the stiffness of the haptic device and thus “feel” the distance to an obstacle before fully committing to travel in that direction. How the distance “feels” can be changed by modifying $\alpha_i$. If $\alpha_i$ is small then more force is felt with a smaller deflection of the haptic end effector as shown in Figure 2.3. A downside of ODDS is that a force is only felt when an input deflection is made and thus gives no indication of a possible collision due to external forces such as wind. This is a minor disadvantage because the algorithms are designed for indoor flight, but this failing is anticipated to be counteracted by adding 3D audio as another feedback modality.

![Figure 2.3: ODDS force vs. displacement with varying $\alpha_i$ values, $d = 1$ m, and $d_{max} = 10$ m.](image)
2.1.3 Velocity Scaled Omni-Directional Dynamic Spring

Depending on the value chosen for $d_{\text{max}}$, and the proximity to obstacles, the stiffness force of ODDS can be too strong or too weak. If $d_{\text{max}}$ is large, then at low velocities the force is too strong when near obstacles. This can make obstacles seem closer then they really are as well as require the operator to exert large forces to make small positional adjustments. On the flip side, if $d_{\text{max}}$ is small, the force of ODDS can be too weak when approaching obstacles at higher velocities. This can cause collisions because the resistance force is not displayed soon and strong enough to adequately warn the operator to slow down and change directions. Even if the operator responds quickly, the deceleration time of the UAV can still cause it to drift into an obstacle.

To help counter these adverse affects, velocity scaled omni-directional dynamic springs, a variation of ODDS, was created in which $d_{\text{max}}$ is scaled by the velocity of the UAV. This modifies equation 2.6 to become:

$$k(d_i) = \frac{s d_{\text{max}} - d_i}{s d_{\text{max}}}, \text{ for } i = x, y, z.$$  \hspace{1cm} (2.8)

where $s$ is the scaling factor that is given by the piecewise function:

$$s = \begin{cases} 
S_L, & \text{if } v \leq V_L \\
av + b, & a = \frac{S_H - S_L}{V_H - V_L}, \quad b = S_H - aV_H, \quad \text{if } V_L < v < V_H \\
S_H, & \text{if } v \geq V_H
\end{cases}$$  \hspace{1cm} (2.9)

$S_L, S_H, V_L,$ and $V_H$ are tunable parameters, where the former two change the lower and upper scaling thresholds and the latter two adjust the break points for the line between the scaling thresholds as shown in Figure 2.4.

VSODDS gives greater fine tuning than ODDS and thus the stiffness force can be designed to be more effective because it also takes into account the velocity of the UAV. If $S_L = S_H = 1$, then VSODDS simply becomes ODDS.
2.2 3D Audio Feedback Algorithms

This section presents two 3D audio feedback algorithms: Continuous Directional Graded Threshold (CDGT), and Discrete Directional Graded Threshold (DDGT). Certain characteristics of these algorithms are inspired by the work done by Lee et al. [26] who investigated using 3D audio cues to help mitigate driver distraction. These methods are designed to be tertiary feedback modalities, after visual and haptic, with the intent to provide useful warning cues without overwhelming the operator’s senses or being too annoying; a difficult balance to achieve.

2.2.1 Continuous Directional Graded Threshold

The Continuous Directional Graded Threshold (CDGT) algorithm works as its name implies. A continuous audio cue (i.e., a long, repeated sound) is displayed only in the direction of the UAV velocity and only when the vehicle is within a threshold distance of an obstacle. In addition, the audio cue is graded, meaning that the volume increases as the UAV approaches the obstacle.
Since it is possible for a UAV to approach multiple obstacles at once, such as walls to the side and to the front if moving diagonally, the velocity vector is decomposed into its x, y, and z components and audio cues can be given simultaneously in those three directions. The directional and threshold aspects of CDGT are intended to reduce overloading the operator’s senses when navigating through small, tight spaces with obstacles all around. If audio cues were displayed in all directions in such situations, then it is likely that the sounds would be overwhelming, annoying, and simply unhelpful.

The volume of the continuous sound is graded in order to help the operator gauge the distance to an obstacle. If the sound is soft and has just started, the operator is near the threshold distance. If the sound is loud, then the operator knows that the obstacle is very close by. The volume level is calculated by the equation:

$$volume = \frac{d}{d_{Thres}} \cdot vol_{min} + \left(1 - \frac{d}{d_{Thres}}\right) \cdot vol_{max},$$  \hspace{1cm} (2.10)

where $d$ is the distance to the obstacle, $d_{Thres}$ is the threshold distance, $vol_{min}$ is the minimum desired volume, and $vol_{max}$ is the maximum desired volume. Thus when $d = 0$, $volume = vol_{max}$ and when $d = d_{Thres}$, $volume = vol_{min}$. The corresponding variables are illustrated in Figure 2.5.

![Figure 2.5: Illustration of CDGT. Audio cue is only sounded in direction of velocity and when UAV is within $d_{Thres}$](image)
2.2.2 Discrete Directional Graded Threshold

Discrete Directional Graded Threshold (DDGT) is similar to CDGT but with a few modifications. First, instead of a continuous sound, a discrete audio cue such as a short duration beep is used. Second, instead of grading the volume, the time period between beeps is graded. Therefore, as the UAV approaches an obstacle, the frequency of the beeping sound increases. Lastly, DDGT uses a nonlinear grading equation that is scaled by the UAV’s velocity. The time between beeps, \( t \), is given by

\[
t = sax^m + b, \quad a = \frac{1 - b}{x_1^m},
\]

(2.11)

where \( m \) is the curve order, \( b \) is a zero offset, \( x_1 \) is the distance from an obstacle when \( t = 1 \), and \( s \) is the scaling factor. Like all the tunable parameters in the algorithms previously presented, \( m, b, \) and \( x_1 \) can be tuned for a certain application or to suit an operator’s preference. Similar to the scaling function for VSODDS, the scaling factor for DDGT is calculated using

\[
s = \begin{cases} 
S_H, & \text{if } v \leq V_L \\
cv + e, & \text{if } V_L < v < V_H, \\
S_L, & \text{if } v \geq V_H 
\end{cases} 
\]

(2.12)

where \( c = \frac{S_H - S_L}{V_H - V_L}, \quad e = S_H - cV_L \).

Again, like VSODDS, \( S_L, S_H, V_L, \) and \( V_H \) are tunable parameters where the former two change the lower and upper scaling thresholds and the latter two adjust the break points for the line between the scaling thresholds. The output of equations (2.11) and (2.12) is shown in Figure 2.6.

The velocity based scaling factor was added to DDGT for similar reasons given for VSODDS. By adding the velocity, the frequency of the discrete audio cue will be faster when approaching obstacles at high velocities thus providing a more severe warning to the operator. In addition, at low velocities the audio cue will not be as urgent when near obstacles and thus will be less annoying.
Figure 2.6: Beep Period vs. Distance and Velocity for DDGT with $m = 1.1$, $b = 0$, $x_1 = 3(m)$, $S_L = 0.1$, $S_H = 1$, $V_L = 0.5(m/s)$, $V_H = 1.0(m/s)$

2.3 Chapter Summary

This chapter presented three haptic feedback algorithms: TTI, ODDS, and VSODDS. TTI is a force feedback algorithm that is based on the time remaining before an impact with an obstacle. The other two are novel stiffness feedback algorithms that are based on the idea that virtual springs are attached to the haptic controller in all directions. Two novel 3D audio feedback algorithms were also presented: CDGT and DDGT. These algorithms provide a 3D audio alert cue only in the direction of the quadrotor velocity and when the quadrotor is within a threshold distance of an obstacle. The implementation of these haptic and audio methods will be discussed in Chapter 4. The results of how ODDS and CDGT performed in a pilot study are given in Chapter 5. The results of the effectiveness of TTI, VSODDS, and DDGT in a human subject experiment are presented in Chapter 6.
CHAPTER 3. BEHAVIORAL ENTROPY

Since one of the main purposes of this research is to determine if multimodal feedback reduces operator workload, it is critical to have a good method for measuring workload. This chapter provides additional background, theory, and the mathematics behind behavioral entropy, an objective measure of workload. It also details how behavioral entropy is implemented in the context of the teleoperation of UAVs in indoor environments. Specific details on selected parameters and implementation of behavioral entropy in a user study is given in Chapter 5. More in-depth detail on behavioral entropy can be found in [2], [35], [40], and [41].

3.1 Background and Overview

Behavioral entropy originates from research done on a method called “steering entropy.” In 1991, Nakayama et al. developed this steering entropy method to easily and accurately calculate the workload imposed on distracted drivers [35]. They found that drivers’ steering behavior is more erratic when performing additional tasks while driving. Using the drivers’ steering angles over time and employing the concept of entropy, Nakayama et al. were able to quantify the erratic behavior of drivers when under high workload. The concept of steering entropy was then generalized to human activity and given the name of behavioral entropy by Boer [40].

Essentially, behavioral entropy works on the idea that humans work to reduce entropy by skilled behavior [2]. A model is created to describe the desired behavior and the error between the model and the actual behavior is used to estimate the behavioral entropy. Higher entropy indicates there is greater deviation in behavior than predicted and thus a higher workload. To implement behavioral entropy in this research, one easy and two hard worlds (tasks) were created for the user study (see Chapter 5 for more detail on the world configurations and experimental setup). The operator’s behavior while navigating a simulated quadrotor in the easy world is used to form the baseline model for behavioral entropy. Data from an operator navigating through the hard worlds
is used to detect deviation from the baseline and thus test the effect of multimodal feedback on workload. The easy world is designed such that the operator is required to use the full range of motion of the haptic device which is needed in order to form a complete baseline model. The linear deflections of the haptic device’s end effector will be used to form the model and calculate the behavioral entropy as discussed in the following sections.

3.2 Model

The first step in implementing behavioral entropy is to create a model that predicts how the operator will use the haptic device to control the UAV. In this research, the quadrotor UAV is controlled by velocities which are commanded to the vehicle when the haptic controller is displaced. Future displacements of the control stick, i.e., future behavior of the operator, can be predicted by using previous displacements made by the operator. There are many different types and degrees of models that use previous inputs to calculate future inputs. Some of these models include Taylor series expansion, ARMA, and state-space models. Using a 3rd order autoregressive (AR) model and considering just \( x \)-direction displacement as an example, the predicted haptic controller displacement at time \( n \), \( \hat{x}_n \), is given by

\[
\hat{x}_n = -a_1 x_{n-1} - a_2 x_{n-2} - a_3 x_{n-3},
\]

(3.1)

where \( x_{n-1}, x_{n-2}, \) and \( x_{n-3} \) are the \( x \)-direction displacements of the previous three time steps. The coefficients \( a_1, a_2, \) and \( a_3 \) are calculated using least-squares regression on the baseline data representing ideal conditions under minimal workload. Figure 3.1(a) illustrates the prediction model. Why an AR model was selected for this research and how it is implemented in the human subject experiment is described in Chapter 5.
Figure 3.1: (a) Example of a 3rd order AR model predicting haptic displacement and (b) the prediction error.

3.3 Model Errors

Once the model has been selected and a prediction sequence has been created from the data and model, the prediction error time series \( \{pe_n\} \) is calculated using

\[
pe_n = x_n - \hat{x}_n.
\]  

(3.2)

An example of a prediction error sequence is shown in Figure 3.1(b). It is the statistical properties of this error sequence that provide the means for quantifying operator workload [2]. Given the prediction error sequence, a histogram of the prediction errors can be created. A probability mass function is then created by normalizing the histogram by dividing each bin by the total count. This probability mass function is an estimate of the prediction error density function \( P(pe; t) \), which is ultimately used to estimate the workload.
The histogram of the prediction errors is created using $2(M+1)$ bins. As given in [41], the set of lower bounds is

$$\{-10e12, -(M) pe_\alpha, -(M-1) pe_\alpha, \ldots, -pe_\alpha, 0, pe_\alpha, \ldots, (M-1) pe_\alpha, (M) pe_\alpha\} \quad (3.3)$$

and the set of upper bounds is

$$\{-(M) pe_\alpha, -(M-1) pe_\alpha, \ldots, -pe_\alpha, 0, pe_\alpha, 2pe_\alpha, \ldots, (M-1) pe_\alpha, 10e12\}.$$ \quad (3.4)

The values of -10e12 and 10e12 are used so that all of the prediction errors are placed in a bin, and $pe_\alpha$ is defined as

$$pe_\alpha = 0.5(|arg\{CDF(pe) = \alpha}\}| + |arg\{CDF(pe) = 1 - \alpha}\}|), \quad (3.5)$$

which represents the absolute prediction error that is greater than $1 - 2\alpha$ percent of all the prediction errors. The widths of the bins can be tuned by changing the value of $\alpha$. If $\alpha$ is chosen to be 0.05, then $pe_\alpha$ is greater than 90% of all the prediction errors. Figure 3.2 provides an illustration of a histogram of the prediction errors and the resulting estimate of the probability density function.

Figure 3.2: (a) Histogram generated from prediction error sequence and (b) the normalized histogram, an estimate of the prediction error density function.
3.4 Behavioral Entropy Calculation

After the prediction error histogram has been normalized, the resulting probability mass function, an estimate of the prediction error density function, is used to calculate the workload. The workload is estimated by considering the information that is contained in the prediction density function. According to information theory, the basis behind behavioral entropy, the more information contained in a system then the greater the uncertainty of specifying the exact state of the system. This means that the more information in the prediction error density function, the more evenly distributed the density function is, which signifies a greater uncertainty in predicting the behavior of the operator. Less predictable behavior is an indication of a higher workload being experienced.

This can be better understood by considering piloting of a UAV through an obstacle course under two different haptic control schemes. Estimates of the prediction error density functions for each control scheme can be obtained as described previously and then compared as shown in Figure 3.3. The bigger spread of the density function of control scheme 1 indicates that there is more information contained in that system, specifically information that is not captured by the model. This additional information signifies that the operator is doing more than predicted by the model and thus is experiencing an increased workload under that control scheme.

Figure 3.3: Prediction error density functions under two haptic control schemes
To quantify the information contained in a prediction error density function, entropy, the average information contained in a system is used. Thus, the behavioral entropy workload estimate is calculated using entropy $H(pe; t)$ defined as

$$H(pe; t) = -\sum_{k=1}^{b} P_k(pe; t) \log_b(P_k(pe; t))$$  \hspace{1cm} (3.6)$$

where $P_k(pe; t)$ is the prediction error probability value associated with bin $k$, and $b$ is the number of bins. A lower entropy, $H(E; t)$, value corresponds to higher performance and thus lower workload. Ultimately it does not matter what base value is used for the log function in (3.6); however, if the base is the same as the number of bins, then entropy values will be scaled between the range $(0, 1)$. An entropy value of 1 could theoretically be obtained if the prediction error density function was uniformly distributed. This would signify that all possible behaviors would equally be likely which is an indication of maximum workload.

### 3.5 Chapter Summary

This chapter summarized the mathematics and theory behind behavioral entropy, an objective measure of workload. Essentially, behavioral entropy uses the error between predicted and actual operator behavior to quantify the workload experienced. The selected parameters and implementation of behavioral entropy in a human subject experiment are described in Chapter 5. The results of the experiment pertaining to behavioral entropy are discussed in Chapter 6. Chapter 7 illustrates how behavioral entropy can be used to examine changes in workload throughout a task.
CHAPTER 4. SIMULATION SYSTEM AND INTERFACE

QuadSim, a quadrotor simulator, was developed as a test bed for examining the effectiveness of multimodal feedback in the control of UAVs. This chapter describes the features of QuadSim as well as other software and hardware used in the simulation system. QuadSim was designed so that it could be used beyond just the scope of this thesis. This means that simulation settings can easily be adjusted, new indoor environments can be created, haptic and 3D audio algorithms can be modified or added and new experiments can easily be designed. This will save effort and development time for future research and experiments.

4.1 System Overview

QuadSim is a multimodal flight simulator of a quadrotor UAV in indoor environments. Figure 4.1 shows the simulation system which consists of:

- SensAble PHANTOM, a commercial haptic force feedback controller that is used to pilot the virtual quadrotor and provide force feedback to the operator.

- Creative Sound Blaster Tactic 3D Alpha stereo headphones to provide 3D audio feedback cues.

- PC computer to provide a graphical user interface (GUI), perform calculations to simulate quadrotor flight, and display a camera view of the virtual world environment.

The PHANTOM and the software used to communicate with it is discussed in section 4.2. More details of the stereo headphones and its software is provided in section 4.3.
As shown in Figure 4.2, the QuadSim software consists of three main components running on the PC: QuadSim Launcher, a MATLAB/Simulink model, and a C++ simulation manager DLL. QuadSim Launcher is the main GUI that appears when QuadSim is started. It allows the user to configure settings and begin a simulation. Once a simulation is started, a MATLAB engine is opened in the background and a Simulink model is started. The Simulink model drives the simulation, solves the quadrotor’s equations of motion, and contains an autopilot function that helps control and maintain stable flight. Each time through the Simulink model loop, a MATLAB C++ MEX S-Function is used to provide quadrotor state information to the C++ simulation manager DLL. The DLL draws the indoor world environment using OpenGL, handles collision detection, and manages and records data. The simulation manager DLL also controls the haptic and 3D audio update loops and interfaces with the PHANTOM and stereo headphones. The Simulink model, simulation manager DLL, and QuadSim Launcher will be described further in sections 4.4, 4.5 and 4.6 respectively.
4.2 SensAble PHANTOM and CHAI 3D

The PHANTOM Premium 1.5 High Force device as shown in Figure 4.3, is a commercial, haptic force feedback controller developed by SensAble Technologies. The PHANTOM provides three degrees of positional sensing (XYZ) with force feedback in those degrees of freedom and is capable of displaying a maximum force of 8.5 N (1.9 lbf). It also includes an encoder stylus gimbal that provides an additional three rotational degrees of freedom (pitch, roll, and yaw). However, it does not provide torsional feedback in the 3 rotational degrees of freedom. The total workspace of the PHANTOM is about 381(15) W x 267(10.5) H x 191(7.5) D mm(inches) which gives of range of motion of the lower arm with pivoting at the elbow [42].
The six degrees of freedom of the PHANTOM make it a suitable device for controlling a quadrotor. The different degrees of freedom of the PHANTOM can be mapped to control the six degrees of freedom of the quadrotor. However, only four of the PHANTOM’s degrees of freedom are required since the forward translation and pitch degrees of freedom are coupled and likewise the lateral translation and roll motions are also coupled. Thus, to control the quadrotor, the following independent commands are required: forward translation or pitch, lateral translation or roll, vertical translation, and yaw angle.

QuadSim has been designed so that the x, y, and z displacements of the PHANTOM’s stylus are mapped into velocity commands in the forward, lateral, and vertical quadrotor directions re-
spectively. The yaw (horizontal rotation) angle of the stylus is mapped to command the quadrotor’s yaw rate. The pitch (vertical rotation) and roll (twist) angles of the PHANTOM are not used.

The PHANTOM is connected to the PC computer through a parallel port and uses CHAI 3D [43] libraries to communicate with QuadSim. CHAI 3D is a set of open source C++ libraries for haptic controllers. The libraries are used to connect and disconnect to the PHANTOM, determine the xyz positions and rotational angles of the stylus, and display forces to the device in the xyz directions. Useful matrix math operations are also provided to aid in axes frame transformations. CHAI 3D also supports several other haptic devices besides the PHANTOM, thus allowing QuadSim the possibility of being used with other commercial devices if desired.

4.3 Stereo Headphones and OpenAL

To display 3D audio feedback cues to the operator, Creative Sound Blaster Tactic 3D Alpha stereo headphones have been selected as pictured in Figure 4.4. The Tactic 3D Alpha is an over-the-head headset with around-the-ear cups. The headphones connect to the computer with a 3.5 mm jack via a USB adapter. The USB adapter bypasses the computer’s sound card and instead provides 360 degree surround sound with THX TruStudio Pro.

![Creative Sound Blaster Tactic 3D Alpha stereo headphones](image)

Figure 4.4: Creative Sound Blaster Tactic 3D Alpha stereo headphones
The 3D audio feedback is implemented in software using OpenAL [44], a C++ open source library that models sounds in three dimensional space relative to the listener. To simulate sound being displayed in three dimensional space, OpenAL uses three main objects: buffers, sources, and a listener as illustrated in Figure 4.5. Audio data are loaded into a buffer and the buffer is attached to one or more sources. The position and orientation of a source determines how the source is heard by the listener. By dynamically updating the positions and orientations of the sources and/or listener, a convincing 3D audio world can be created [45].

![Diagram showing relation of the fundamental OpenAL objects.](image)

Figure 4.5: Diagram showing relation of the fundamental OpenAL objects.

### 4.4 Simulink Model

When a simulation is started in QuadSim Launcher, a MATLAB engine is started which runs a specially designed Simulink model. The Simulink model is what drives the simulation by using a loop to calculate the quadrotor dynamics, model collisions, and provide stabilized flight through an autopilot. A high level block diagram of the Simulink model is shown in Figure 4.6. The simulation loop is run at 30 Hz and is composed of three main blocks: an autopilot function, a quadrotor dynamics function, and a C++ MEX S-Function to communicate with the simulation
manager DLL. Essentially, displacements from the PHANTOM are converted to desired velocity commands which are outputs of the S-Function block. The commanded velocities with the current states are passed into the autopilot block where quadrotor motor commands are calculated. The quadrotor dynamic block uses the autopilot commands and the distances to obstacles to update the quadrotor states. The updated quadrotor states are then used in the S-Function by the simulation manager DLL to draw an updated view of the simulated environment. The RTBlock [46] is used to slow the simulation loop to run in near real time.

![Simulink block diagram](image)

Figure 4.6: Simulink block diagram used to simulate the quadrotor.

### 4.4.1 Autopilot Block

The autopilot function used in the Simulink model was originally created by Dr. Randal Beard, an Electrical Engineering professor at Brigham Young University. Brandt, for his Master’s Thesis, modified the function by changing some of the control loops and gains [1]. This thesis uses the same autopilot function as modified by Brandt.

The autopilot uses the velocity commands and the quadrotor states in PD loops to generate quadrotor motor commands. One of the PD loops calculates the desired roll and pitch angle by comparing the desired velocity with the actual velocity. Another PD control loop then takes the desired roll and pitch angles compared with the actual angles to calculate the body $x$ and $y$ axes torques. The $z$ axis torque is calculated using another PD loop with the comparison of the desired
and actual yaw rate. The autopilot function outputs motor commands which are determined by multiplying the thrust and torques with known parameters of the quadrotor such as the moments of inertia and mass [1].

4.4.2 Quadrotor Dynamics Block

The quadrotor dynamics block receives the motor commands from the autopilot and calculates the forces and torques that act on the quadrotor. These forces and torques are then used in the quadrotor’s equations of motion to calculate the quadrotor states. The equations of motion were derived by Dr. Randal Beard [47] and are given by

\[
\begin{pmatrix}
\dot{p}_n \\
\dot{p}_e \\
\dot{h}
\end{pmatrix} =
\begin{pmatrix}
c \theta c \psi & s \phi s \theta c \psi - c \phi s \psi & c \phi s \theta c \psi + s \phi s \psi \\
c \theta s \psi & s \phi s \theta s \psi + c \phi c \psi & c \phi s \theta s \psi + s \phi c \psi \\
s \theta & -s \phi c \theta & -c \phi c \theta
\end{pmatrix}
\begin{pmatrix}
u \\
v \\
w
\end{pmatrix}
\tag{4.1}
\]

\[
\begin{pmatrix}
\dot{u} \\
\dot{v} \\
\dot{w}
\end{pmatrix} =
\begin{pmatrix}
rv - qw \\
pw - ru \\
qu - pv
\end{pmatrix} + \frac{1}{m}
\begin{pmatrix}
f_x \\
f_y \\
f_z
\end{pmatrix}
\tag{4.2}
\]

\[
\begin{pmatrix}
\dot{\phi} \\
\dot{\theta} \\
\dot{\psi}
\end{pmatrix} =
\begin{pmatrix}
1 & \sin \phi \tan \theta & \cos \phi \tan \theta \\
0 & \cos \phi & -\sin \phi \\
0 & \frac{\sin \phi}{\cos \theta} & \frac{\cos \phi}{\cos \theta}
\end{pmatrix}
\begin{pmatrix}
p \\
q \\
r
\end{pmatrix}
\tag{4.3}
\]

\[
\begin{pmatrix}
\dot{p} \\
\dot{q} \\
\dot{r}
\end{pmatrix} =
\begin{pmatrix}
\frac{J_z - J_y}{J_z} qr \\
\frac{J_x - J_z}{J_y} pr \\
\frac{J_x - J_z}{J_z} pq
\end{pmatrix} + \frac{1}{J_z} \begin{pmatrix}
\tau_\phi \\
\tau_\theta \\
\tau_\psi
\end{pmatrix}
\tag{4.4}
\]

where \(p_n, p_e\) are the inertial north and east positions of the quadrotor; \(h\) is the altitude of the quadrotor; \(u, v, w\) are the body frame velocities; \(\phi, \theta, \psi\) are the roll, pitch, and yaw Euler angles; and \(p, q, r\) are the roll, pitch, and yaw Euler angle rates. These equations of motion are complex, non-linear equations and are solved by Simulink’s built-in ODE solver. One of the main reasons for using MATLAB’s engine and Simulink is to provide a robust method for solving these complex equations of motion.
The quadrotor dynamic block also receives as an input the distances to surrounding obstacles. These range measurements are calculated by the collision detection algorithm in the simulation manager DLL. The distances are used to modify the quadrotor dynamics in order to simulate collisions and prevent the quadrotor from passing through obstacles.

4.5 Simulation Manager DLL

The simulation manager DLL that is called in the MEX S-Function of the Simulink model, is the heart of the entire simulation. The DLL manages drawing the camera view of the world environment using OpenGL; handles collision detection by using ray casting techniques; controls the haptic and 3D audio feedback loops; and manages and records the simulation data.

4.5.1 World Drawing using OpenGL

One of the primary responsibilities of the simulation manager DLL is to provide a virtual camera view of the indoor environment as shown in Figure 4.7. The camera is fixed on the body x-axis of the quadrotor and faces in the direction of forward movement. The indoor world environment is drawn using OpenGL, a powerful API that can create visibly rich and realistic graphics. The quadrotor state information calculated by the ODE solver in the Simulink model is used by OpenGL code to rotate and translate the world objects which makes it appear as if the quadrotor is flying through the indoor environment. The graphical display is updated at 100 Hz. Although it would have been more convenient to create the graphics using MATLAB/Simulink, OpenGL was chosen for two reasons. First, OpenGL is able to provide more realistic graphics then MATLAB and thus provide a higher fidelity representation of a real-world environment. Second, by having the graphics separated from MATLAB, they can also be used to provide a virtual camera view for a physical quadrotor thus allowing the graphics to be used in both simulated and physical implementations.

An indoor environment can be designed through the use of XML code. Special XML tags have been custom made for QuadSim to facilitate the easy creation of box objects and QUAD polygons. Any number of boxes and QUADs can be positioned, rotated, scaled, and combined together to create a virtual indoor environment. Colors and textures can easily be added to the
world polygons to make the world appear more realistic. Since the world polygons are not hard coded into the simulation DLL but are custom made, the scope of QuadSim is not limited to just this thesis but can also be used to simulate quadrotor flight in other indoor environments for future studies. The indoor environments created for the user study in this thesis are presented in Chapter 5.

4.5.2 Collision Detection

The simulation manager DLL also handles collision detection by implementing techniques and code provided in [48]. The collision detection works by calculating the distances to surrounding obstacles. The distances to obstacles are calculated using ray casting techniques. Ray casting works by mathematically projecting a ray in a desired direction and then calculating the distance to where the ray intersects with the plane formed by the closest world polygon. The point of intersection is also calculated and used to determine if the intersection point is within the polygon thus detecting if the ray actually intersects with the world object. To find distances to obstacles around the quadrotor, the simulation manager casts rays originating from the quadrotor’s center of mass in six directions relative to the quadrotor body frame: forward, backward, left, right, up, and down.
If the distance to an obstacle in one or more of these directions is zero, the quadrotor dynamics block in the Simulink model (see Section 4.4.2) simulates a collision and prevents the quadrotor from passing through the object. The range measurements in these six directions are also used in the haptic and 3D audio feedback algorithms.

In general, ray casting requires checking the ray with every world polygon in order to find the distance to the closest intersecting polygon, if any exist. This type of exhaustive search can be computationally expensive, especially if there are thousands of world polygons and multiple rays being casted. Instead of doing an exhaustive search, the world polygons are divided into a leaf-storing binary space partitioning (BSP) tree. A BSP tree is a binary structure that partitions the world environment space into pairs of subspaces with respect to dividing planes. In a leaf-storing BSP tree, the polygons are stored in the leaves of the tree and the dividing planes are stored in the internal nodes. An example of a BSP for a simple 2D world is shown in Figure 4.8. Intersecting a ray against a BSP tree only requires searching a subset of the entire world polygons which greatly improves execution speed and performance over an exhaustive search. More information on ray casting and BSP trees can be found in [48].

![Figure 4.8: Example of creating a BSP tree for a simple 2D indoor environment with (a) one dividing plane and then (b) recursively adding two more dividing planes.](image-url)
4.5.3 Haptic and 3D Audio Loops

The management of the haptic and 3D audio update loops are also controlled by the simulation manager DLL. Both update loops run in their own thread. Each thread is given higher priority over all other threads so that they execute faster and thus provide better feedback response to the operator. The simulation DLL communicates with the PHANTOM via CHAI 3D and communicates with the stereo headphones via OpenAL as discussed in Sections 4.2 and 4.3 respectively.

The actual algorithms discussed in Chapter 2 to calculate the force and 3D audio feedback cues displayed to the operator are not contained within the simulation manager DLL but in separate DLLs: one for the haptic feedback algorithms and one for the 3D audio feedback algorithms. The simulation manager DLL’s haptic and 3D audio update loops in turn call these separate DLLs to update the forces and audio cues displayed to the PHANTOM and stereo headphones, respectively. The haptic and audio algorithms were modularized in separate DLLs so that new algorithms could easily be added to QuadSim. If a new haptic algorithm, for instance, is added, then only the haptic algorithm DLL needs to be rebuilt and not the entire QuadSim project. This again makes QuadSim extendable and easy to use with future research and experiments.

4.5.4 Data Manager

All of the simulation system data such as settings, world polygons, range measurements, haptic forces, and quadrotor states are stored and managed by the simulation DLL. Data needed for post simulation analysis such as simulation time, quadrotor states, and if the quadrotor is in a collision, is saved and recorded to a text file at 8 Hz. The data to be recorded is pushed onto a list array and then in a separate thread the contents of the list are written to a file. The separate thread is needed to prevent the simulation from slowing down since writing to a file is an inherently slower task.

4.6 QuadSim Launcher

QuadSim Launcher is the main user interface that brings all of the features of QuadSim together. It provides GUIs for changing simulation settings, beginning a free/test flight, creating and launching a set of flights used for experiments, and viewing the world environments with flight
path data. All of these features can be accessed by the main menu as shown in Figure 4.9. More details for each feature of QuadSim Launcher is discussed in the following sections.

![QuadSim Launcher](image)

Figure 4.9: QuadSim main menu.

4.6.1 Settings

The simulation settings for QuadSim can be changed and saved in the settings menu as shown in Figure 4.10. The settings menu consists of four tabs: general, quadrotor, haptics, and 3D audio. The general tab allows the user to change the simulation screen dimensions or display in fullscreen. In the quadrotor tab, the user is able to change the dimensions of the quadrotor as well as the maximum commandable linear and angular velocities. The minimum and maximum detection distances to obstacles can also be changed in the quadrotor tab. The haptics and 3D audio tabs provides fields for entering the parameters for the algorithms discussed in Chapter 2. All the settings can be saved and loaded under a profile name. Thus, profiles for each testing configuration or experiment can be created and easily changed between.
4.6.2 Free Flight

The free flight menu permits a user to launch a simulation under a desired configuration. Launching the simulation under the free flight menu is useful for testing different indoor world environments, tuning haptic and 3D audio algorithm parameters, and for any other testing purpose. On the free flight menu screen, the user is able to change the desired world, settings profile, and dynamics mode as shown in Figure 4.11. The two available dynamics modes are NONE and MATLAB. The NONE mode uses just the kinematic model to simulate quadrotor movement; whereas, the MATLAB mode uses the full quadrotor kinematic and dynamics equations to simulate flight as discussed in Section 4.4.2. The user is also able to select the desired haptic and 3D audio devices with the desired feedback algorithms. If no haptic device is connected or selected, then the user is able to control the quadrotor using the keyboard. Finally, the user is also able to select whether collision detection is enabled and name the file for the output flight data.
4.6.3 Experimental Flight and Experiment Creator

While the free flight menu is useful for testing multimodal flight configurations, it would be tedious to use when performing an experiment where each subject is required to perform multiple flights under different configurations. Therefore, the experimental flight menu and experiment creator were designed to make running experiments with QuadSim much easier.

The experimental flight menu as shown in Figure 4.12(a), allows the user to start an experiment. An experimental flight consists of multiple simulation runs one after another with optional transition screens in between. When starting an experiment, the user or experiment administrator is able to select which experiment to run, the settings profile, the dynamics mode, and the desired haptics and audio devices. Once the experiment is started, the subject information screen as shown in Figure 4.12(b) is presented. This screen collects and saves information about the subject performing the experiment.

The experiment creator screen shown in Figure 4.13 allows a designer to create a series of simulation runs and/or transitions. This facilitates the simple design and development of experiments which requires multiple flights under different configurations. When a run is added to the experiment, the designer is able to select the world environment, haptic and audio feedback algo-
Figure 4.12: (a) QuadSim experimental flight menu and (b) QuadSim subject information screen.

Figure 4.13: QuadSim experiment creator menu.

algorithms, and select if it is to be randomized. If multiple runs in a row are selected to be randomized, then that block of runs will appear in a randomized order when the experiment is being executed by a subject. When a transition is added, the designer is able to select which transition slide is shown. Any PNG image can be used as a transition slide and thus the experiment designer can create any desired transition screen. Also, if the experiment designer desires to use the NASA TLX to measure workload, a NASA TLX rating transition screen can be shown after each run along with a
NASA TLX weighting screen at the end of the experiment. An example of the NASA TLX screens are shown in Figure 4.14. Ratings files and a weighting file are saved from the NASA TLX screens and can be used to calculate the workload score as described in [37].

![Image of NASA TLX screens]

Figure 4.14: (a) NASA TLX rating transition screen and (b) NASA TLX weighting transition screen.

### 4.6.4 World Viewer

The final feature of QuadSim Launcher is the world viewer which shows an overhead view of any world file. If the output file of a simulation flight is loaded, world viewer will show white dots representing the quadrotor’s path as shown in Figure 4.15. Red dots indicate that the quadrotor collided with an obstacle. The view of the world can be rotated, panned, and zoomed in or out. The world viewer also indicates the number of collisions and the total flight time. World viewer is not only useful for visualizing the quadrotor’s path but also for viewing the entire world when creating a new indoor environment.
4.7 Chapter Summary

This chapter presented QuadSim, a complex and robust quadrotor simulator. QuadSim interfaces with the PHANTOM haptic controller using CHAI 3D and stereo headphones using OpenAL to provide a multimodal test bed. The quadrotor dynamics are simulated using MATLAB/Simulink and collision detection is handled using ray casting techniques. Realistic indoor environments are displayed using OpenGL. QuadSim is also highly versatile making it usable for future studies. Chapter 5 discusses how QuadSim is used in a human subject experiment. Recommended improvements to QuadSim are presented in Chapter 7.
CHAPTER 5. HUMAN SUBJECT EXPERIMENT

A human subject experiment was conducted to examine the effectiveness of multimodal feedback in the teleoperation of a quadrotor UAV in cluttered indoor environments. This chapter reviews the purpose of the study; describes the experimental setup, design, and measures; and provides more details on how behavioral entropy was implemented in the experiment.

5.1 Purpose

The objective of this research is to determine the effectiveness of using multiple sensory modalities as means of providing additional information about the indoor environment to operators of UAVs. Specifically, the experiment aims to study the effects of augmenting visual feedback with haptic force feedback and 3D audio alert cues. The primary effects of interest are the number of collisions and operator workload.

The hypothesis of the experiment is that multimodal feedback employing both haptic and 3D audio feedback will reduce the number of collisions while controlling a quadrotor in an indoor environment in addition to reducing the operator’s workload.

5.2 Experimental Apparatus

The experiment was conducted in the MAGICC lab on Brigham Young University’s (BYU) campus. The subjects performed the experiment using a multimodal workstation as pictured in Figure 5.1. As described in Chapter 4, the multimodal workstation is comprised of a PC computer running QuadSim, the SensAble PHANTOM haptic device, and Creative Sound Blaster Tactic 3D Alpha stereo headphones. The PC computer used to run the simulation is a Dell Precision PWS 690 with 3.2 GHz dual-core Intel Xeon 5100 series processors, 2 GB of RAM, and a NVIDIA FX 3450/4000 SDI graphics card. The simulated quadrotor’s camera view is displayed on a 19 inch Dell flat panel monitor. The display was set to 1280 x 1024 pixels with 32 bit color resolution. The
Figure 5.1: Multimodal workstation used in the human subject experiment.

PHANTOM was placed to the right of the monitor and was used to control the quadrotor as well as to display the haptic force feedback to the subject. The Creative Sound Blaster stereo headphones provided the 3D audio alert cues and were worn by the subject throughout the experiment.

5.3 Pilot Study

Prior to the experiment, a pilot study was conducted. The purpose of the pilot study was to tune parameters, debug the system, and verify that correct measurements and reasonable results were obtained. The observations and results from the pilot study were important factors in the design of the final human subject experiment.

The pilot study utilized the experimental apparatus as discussed in the previous section. Eight male graduate students from BYU’s MAGICC lab participated voluntarily in the study. The study was a balanced two factor experiment. The first factor was haptic feedback with three levels: no feedback, feedback using the TTI algorithm, and feedback using the ODDS algorithm. The second factor was 3D audio and had two levels: no audio feedback and feedback using the CDGT algorithm. Each subject performed nine runs of flying the simulated quadrotor through a virtual
indoor obstacle course with the primary objective of completing the course without any collisions and the secondary objective to complete it as fast as possible. The first run was a practice run and was performed on an “easy” obstacle course. The second and ninth runs were also done on the easy world and served as baseline runs in calculating the workload using behavioral entropy. Runs three through eight consisted of random combinations of the factors and levels and each one was performed on the “hard” course which was designed to be more difficult. After each run, the subject rated their perceived workload for the run using the six NASA TLX rating scales. At the end of all nine runs, the subject gave an importance weighting to each scale. The ratings and weightings were then used to calculate the NASA TLX workload score. The workload score for behavioral entropy was calculated post hoc and used each subject’s haptic stick deflection data.

The results of the study strongly suggest that haptic feedback does reduce the number of collisions as compared with no haptic feedback. The results were less clear with workload but there was an indication that the ODDS haptic algorithm helped reduce workload. The 3D audio feedback caused more variance in the data and did not appear to be beneficial in reducing the number of collisions or workload. It is important to note that the results of the pilot study cannot be extended to a more general population (which was not the intent of the study) due to the small sample size, use of just one hard world environment, and bias of subjects since many were familiar with this research. However, the following useful observations were gained:

- A small auto-centering force is needed return the haptic control stick back to zero deflection when haptic feedback is not present. Many of the subjects had a hard time finding the neutral/zero deflection position of the device which was a source of frustration. Most normal (i.e., non haptic) control sticks have a natural centering force. This feature was included in the final experiment.

- The force calculated by the TTI algorithm was too strong and needed to be tuned down.

- The ODDS force was too stiff at times, especially when near obstacles at low velocities. This would make it hard for the operator to make small positional adjustments when near obstacles. This observation led to the development of VSODDS as discussed in 2.1.3.

- The CDGT 3D audio feedback algorithm was not helpful in avoiding collisions or reducing workload. In particular, the graded volume of the continuous sound was not distinctive
enough to help subjects gage the distance to obstacles, especially at high velocities. This observation led to the development of the DDGT algorithm as discussed in 2.2.2.

- More than one “hard” world was needed in order to generalize the effects of haptic and 3D audio feedback.

As mentioned before, the results and observations of the pilot study were used to improve the design of the final human subject experiment as discussed in the next section.

### 5.4 Experimental Design

The human subject experiment was designed in consultation with the BYU Center for Collaborative Research and Statistical Consulting. This section presents the main components of the design of the experiment, including the factors and levels, algorithm parameter selection, indoor environments, participants, and procedure.

#### 5.4.1 Factors and Levels

The study was designed to be a mixed factorial experiment with the following factors and levels:

- **Factor 1: haptic feedback algorithm**
  - Levels: no haptics, TTI feedback, VSODDS feedback

- **Factor 2: 3D audio feedback algorithm**
  - Levels: no audio, DDGT feedback

- **Factor 3: Indoor Environment**
  - Levels: hard world 1, hard world 2

These factors and levels are slightly different than those for the pilot study. The VSODDS haptic algorithm was chosen to replace ODDS since it was designed after the pilot study with the intent to improve the sensitivity of ODDS. Likewise, the DDGT 3D audio feedback algorithm replaced
CDGT since CDGT performed poorly in the pilot study. Also, to better generalize the results, a second indoor environment was created, which added a third factor to the experimental design. These changes reflect the insights gained from the pilot study as previously discussed in Section 5.3.

There are twelve possible combinations of the three factors. Ideally, all subjects would perform a simulation run for each combination. However, due to time constraints, each subject performed only six runs, which makes the experiment unbalanced. The six runs included all of the possible haptic and audio level combinations with each run alternating between the two world environments. Thus, every subject performed each haptic level twice, once with each audio level, and each world environment three times. The run order for each subject was randomized to mitigate the effects of ordering and learning.

### 5.4.2 Haptic and 3D Audio Parameters

The parameters for the different haptic and 3D audio feedback algorithms were tuned for the experiment based on intuition, repeated testing, and the observations from the pilot study. When the no haptic feedback level is being experienced, a small spring force with a spring constant of $10.0 \, N/m$ is displayed to help center the device. The selected parameters for TTI, VSODDS, and DDGT as described in Chapter 2 are presented in Tables 5.1, 5.2, and 5.3 respectively. The VSODDS values for $f_{\max_i}$, $x_{\max_i}$, and $\alpha_i$ are the same in the $x$, $y$, and $z$ directions.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$k$</td>
<td>0.85 $Ns$</td>
</tr>
<tr>
<td>$F_{\max}$</td>
<td>6.0 $N$</td>
</tr>
<tr>
<td>$R$</td>
<td>0.1 $m$</td>
</tr>
</tbody>
</table>

Table 5.1: TTI haptic feedback algorithm parameters.
Table 5.2: VSODDS haptic feedback algorithm parameters.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$d_{max,x}$</td>
<td>10.0 $m$</td>
</tr>
<tr>
<td>$d_{max,y}$</td>
<td>4.0 $m$</td>
</tr>
<tr>
<td>$f_{max}$</td>
<td>6.0 $N$</td>
</tr>
<tr>
<td>$s_{max}$</td>
<td>0.1 $m$</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>0.3</td>
</tr>
<tr>
<td>$S_H$</td>
<td>1.0</td>
</tr>
<tr>
<td>$S_L$</td>
<td>0.2</td>
</tr>
<tr>
<td>$V_H$</td>
<td>2.0</td>
</tr>
<tr>
<td>$V_L$</td>
<td>0.3</td>
</tr>
</tbody>
</table>

Table 5.3: DDGT 3D audio feedback algorithm parameters.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$d_{Thres}$</td>
<td>10.0 $m$</td>
</tr>
<tr>
<td>$x_1$</td>
<td>3.0 $m$</td>
</tr>
<tr>
<td>$m$</td>
<td>1.1</td>
</tr>
<tr>
<td>$b$</td>
<td>0.0</td>
</tr>
<tr>
<td>$S_H$</td>
<td>1.0</td>
</tr>
<tr>
<td>$S_L$</td>
<td>0.1</td>
</tr>
<tr>
<td>$V_H$</td>
<td>1.0</td>
</tr>
<tr>
<td>$V_L$</td>
<td>0.5</td>
</tr>
</tbody>
</table>

5.4.3 Indoor World Environments

Since the purpose of the experiment is to explore multimodal feedback for piloting a quadrotor in indoor environments, three simulated indoor worlds were created. The worlds were designed to be enclosed courses with obstacles cluttering the path. The subject is required to fly the quadrotor from one end of the obstacle course to the other. Since one of the worlds contains fewer obstacles making it less difficult, it is designated as the easy world. The other two worlds are referred to as hard world 1 and hard world 2 or just simply worlds 1 and 2.

The obstacles in worlds 1 and 2 were designed to simulate obstacles that might be found in a real indoor environment such as doorways, narrow hallways, pillars, furniture, overhangs, and stairs. Wind was also added in a few sections to make the courses more difficult and to study how the haptic and 3D algorithms respond to external forces.
World 1 is pictured in Figure 5.2. The quadrotor starts behind Obstacle 1, which is a pillar in the middle of the hallway forcing the operator to enter the doorway of Obstacle 2 from the side. Obstacle 3 contains a narrow hallway to test how the algorithms respond to tight spaces. At the end of the hallway is a curved wall to examine how the algorithms respond to a non straight surface. The operator must then navigate over Obstacle 4 and under Obstacle 5 and then avoid the jagged wall (Obstacle 6) while turning right. Obstacle 7 is a rotated doorway which requires the operator to either yaw before moving forward or to translate at a diagonal. The operator then approaches Obstacle 8, which is two outcroppings from the hallway. Obstacle 9 is an area with 0.5 m/s wind blowing the quadrotor from left to right, making it more difficult to enter the narrow doorway of Obstacle 10, which is a section with multiple pillars. After Obstacle 10, there is another section of wind blowing from right to left at 0.75 m/s (Obstacle 11). Finally, the operator must adjust for the wind and navigate through the narrow tunnel that is Obstacle 12. The run automatically ends once the quadrotor is within a few meters of the red wall.

Figure 5.2: Overhead view of hard world 1.
As pictured in Figure 5.3, world 2 was designed to have a similar difficulty as world 1. It was also designed to require the quadrotor to have more changes in elevation. World 2 starts with Obstacle 1, which is a series of three rotated doorways similar to Obstacle 7 in world 1. Obstacle 2 is a flight of stairs that wrap around a corner. A flight of descending stairs (Obstacle 3) then follows. Both sets of stairs have slanted ceilings. The operator must then navigate up, across, and then down Obstacle 4 followed by a sharp left turn. Obstacle 5 is a section of 0.75 m/s wind intended to make it more difficult to enter the doorway (Obstacle 6) of the following hallway. The narrow hallway of Obstacles 7 and 8 is designed to test how the algorithms respond to a long section of a tightly enclosed space with sharp turns and angles designed to make it difficult for the quadrotor to stay in the middle of the hallway. Obstacle 9 is another section of 0.75 m/s wind that blows the quadrotor towards Obstacle 10. Again, the run ends once the quadrotor is within a few meters of the red wall.

Figure 5.3: Overhead view of hard world 2.
The easy world is used when forming a baseline model for calculating the behavioral entropy workload by representing an ideal, unloaded condition. The easy world, as shown in Figure 5.4, is designed such that the operator is required to use the full range of motion of the haptic device which is needed in order to form a complete baseline model. More detail on how the easy world is used with calculating behavioral entropy is given in Section 5.6.

![Figure 5.4: Overhead view of the easy world.](image)

### 5.4.4 Participants

Based on a power study performed using the pilot study data, it was estimated that a minimum of sixteen participants were needed for the experiment. Seventeen participants were recruited, of which four were female. The participants’ ages ranged from 20 to 29 with an average age of 24. Twelve of the participants were students in the Mechanical Engineering department at BYU and the other five were Psychology students. Each participant was right handed and had
good hearing. Prior to the experiment, every participant rated their amount of experience with joysticks, video gaming, RC helicopters, and flight simulators from 0 to 10 with 0 signifying no experience and 10 representing a lot of experience. The participants’ experiences ranged from 0 to 10 with an average of 5.12. Participation in the experiment was strictly voluntary and no monetary compensation was given.

5.4.5 Procedure

The experiment was performed with approval from BYU’s Institutional Review Board (IRB) for Human Subjects. Before participating in the experiment, each volunteer was given adequate time to read and sign a consent form. The volunteer was then situated in front of the multimodal workstation (see Figure 5.1) and was asked to complete the subject information form as shown in Figure 4.12(b). The purpose of the experiment was explained and instructions were given. First, a description of a quadrotor was given and the omni-directional flight capabilities of the quadrotor were explained. The PHANTOM haptic controller was then explained along with a brief description of the types of forces it would display during the experiment. The basics of how 3D audio works was also explained and details were given on how to use the 3D audio alert cues to avoid collisions. Next, the user was given a demo on how to start a simulation run and how to control the quadrotor using the PHANTOM. The demo also showed the user how use the NASA TLX rating screens as shown in Figure 4.14. It was then explained that the user would perform six runs alternating between the two hard worlds with random combinations of haptic and 3D audio feedback. The objectives were explained as first: complete the course with the least number of collisions possible and second: complete the course as fast as possible. Finally, each subject was made aware that wind was present in various sections of each world.

None of the participants had ever seen or used the simulator prior to the experiment. In order to familiarize each subject with the simulator and the layout of the worlds, every subject performed two practice runs: one on world 1 and one on world 2. No haptic nor 3D audio feedback was given on the practice runs. After the practice runs, each subject then performed a block of six runs that contained a random ordering of all the possible haptic and audio level combinations and alternating between worlds 1 and 2. After each run, the subject rated their perceived workload using the NASA TLX. After completing the block of six runs, the subject performed one more
run on the easy world with no haptic and no 3D audio feedback. The easy world run represents an ideal, unloaded condition where the workload is minimal. Finally, the subjects finished the experiment by giving weightings to the NASA TLX rating scales. The experiment for each subject lasted between 45 and 60 minutes. After the experiment, and if the subjects were willing, verbal questions were given to assess their perceived effectiveness of the multimodal feedback and their overall experience.

5.5 Measures

To determine the effectiveness of the multimodal feedback, several measures were recorded. These measures are divided into two categories, primary and secondary. The primary measures are those of most interest and the secondary provide additional information to help gauge the effectiveness of the feedback. The primary measures are described as follows:

- **Number of Collisions**: the total number of times that the quadrotor hits an obstacle. Since the quadrotor can scrape along an obstacle, each continuous section of hits is counted only as one collision.

- **Collision Length**: the total sum of the lengths of continuous collisions. Each collision length is calculated using the Euclidean distance between hit points at each time step.

- **Behavioral Entropy XYZ Workload**: the operator workload calculated using behavioral entropy. This measure is recorded for the x, y, and z directions separately. More detail on this measure is given in Section 5.6.

The secondary measures are:

- **NASA TLX Workload**: the overall operator workload using the NASA TLX.

- **Total Time**: the time it took to complete the run.

- **Total Time Normalized**: the time it took to complete the run divided by the minimum path length for each course respectively. Since the path lengths of the worlds are different, this measure is used to be able to compare the total time between worlds.
• Path Length: the total distance traveled by the quadrotor during the run.

• Path Length Normalized: the total distance traveled by the quadrotor during the run divided by the minimum path length of the world. This measure is used to be able to compare the path lengths between the different worlds.

• Average Velocity: the overall average velocity of the quadrotor throughout the entire run.

• Standard Deviation of Velocity: the standard deviation of the average velocity for each run.

• Average Force: the Euclidean average force displayed by the PHANTOM throughout the entire run.

• Standard Deviation of Force: the standard deviation of the average force displayed by the PHANTOM for each run.

• Average Haptic Device Displacement: the average distance that the haptic control stick was displaced from its zero position throughout the entire run.

• Standard Deviation of Haptic Device Displacement: the standard deviation of the average haptic control stick displacement for each run.

5.6 Behavioral Entropy Implementation

As explained in Chapter 3, the behavioral entropy workload measure is calculated by using the error between a model of predicted operator behavior and the actual behavior. The linear $x$, $y$, and $z$ haptic control stick deflection data for each subject are used in three separate models to predict future deflections in those directions. Thus, a behavioral entropy workload is calculated for each direction separately. The following discussion and selected parameters are the same for each direction and for each subject.

A third order AR model using the haptic control stick deflection was selected to predict future deflection as given in (3.1). An AR model was chosen based on work done in [41] and a third order was chosen so that enough previous data could provide a good prediction without focusing too much on the noise as a higher order would. The AR coefficients were calculated using a batch least-squares regression on the data from the easy world run. Coefficients were calculated
for each subject using their respective easy world data. The easy world data and prediction model for each subject were then used to calculate the prediction error sequence using (3.2). The resulting sequence represents the baseline prediction error for each subject. The baseline prediction error sequence was then used to create the histogram bins as described in Section 3.3. Nine bins and a $pe_a$ value of 0.9 were used in creating the bin edges. These parameters were selected based on a user study performed in [2].

Prediction error sequences were generated for each of the six runs on the hard worlds for each subject. These runs represent loaded runs, whereas the easy world run represents an ideal, unloaded run with minimal workload. The prediction error sequence for each loaded run was turned into a histogram using the binning scheme created from the baseline prediction error sequence. The histograms were normalized to form estimates of the prediction error density functions as described in Section 3.2. Finally, the prediction error density function for each run was used in (3.6) to calculate the behavioral entropy workload score for that run.

The behavioral entropy workload measures for the $x$, $y$, and $z$ directions were calculated offline after the entire experiment was performed. Prior to estimating the AR coefficients, the raw data were filtered using a 5th order low-pass Butterworth filter with a cutoff frequency of $3/7 f_s$. The data was then downsampled to 4 Hz as recommended in [41].

5.7 Chapter Summary

This chapter discussed the purpose, experimental apparatus, and design for the human subject experiment. The various measures for the experiment as well as the implementation of behavior entropy in the study were also explained. The details of the statistical analysis and results of the experiment are presented next in Chapter 6.
CHAPTER 6. RESULTS AND DISCUSSION

This chapter presents the statistical analysis and results from the experiment described in Chapter 5. It also provides discussion on the key elements of the results.

For the data analysis, all the runs of Subject 15 and run 6 of Subject 8 were dropped. The data for Subject 15 had extreme outliers for multiple runs in several measures. The most extreme outliers was 4.39 standard deviations from the mean. Furthermore, after careful review of the data and information provided by Subject 15, it was determined that the subject had less experience with joysticks, flight simulations, and video gaming than the intended population of the study, thus warranting removal. Run 6 of Subject 8 was also removed due to hardware malfunction with the PHANTOM during the run. In total, 95 runs were used for the data analysis.

The analysis of the data was performed with the aid of the BYU Center for Collaborative Research and Statistical Consulting. The data was analyzed using a mixed model analysis of variance with blocking on subject. This model accounts for lack of independence between samples since each subject has six samples instead of one. The analysis also treats each subject as their own control. Each subject also acts as his or her own block, thus the analysis accounts for the variation between subjects and identifies any correlations between them. Even though one subject might be more experienced and perform better than another, the analysis identifies if the haptic or audio feedback helped improve performance for both subjects.

An $\alpha$ value of 0.01 was chosen as the cutoff for statistical significance. Typically a 95% confidence interval with a corresponding $\alpha$ value of 0.05 is chosen. However, since this analysis makes multiple comparisons of means, the confidence placed on the result decreases. To adjust for this, a psuedo Bonferroni correction [49] was made which resulted in an $\alpha$ value of 0.01. Thus any p value less than 0.01 is considered statistically significant. If a factor for a measure is considered significant, the means of the different levels were compared using the Tukey-Kramer comparisons
test [49], again with an $\alpha$ value of 0.01. The resulting significant effects for all measures are listed in Table 6.1. Details of each measure will follow.

Table 6.1: Effect p values for all measures. Significant effects in bold ($\alpha = 0.01$).

<table>
<thead>
<tr>
<th>Measure</th>
<th>Haptics</th>
<th>Audio</th>
<th>World</th>
<th>Haptic*World</th>
</tr>
</thead>
<tbody>
<tr>
<td>Num Collisions</td>
<td>0.009</td>
<td>0.1304</td>
<td>0.0305</td>
<td>NA</td>
</tr>
<tr>
<td>Collision Length</td>
<td>&lt;.0001</td>
<td>0.5580</td>
<td>0.0028</td>
<td>NA</td>
</tr>
<tr>
<td>BE Workload X</td>
<td>0.0105</td>
<td>0.0526</td>
<td>0.7657</td>
<td>0.0084</td>
</tr>
<tr>
<td>BE Workload Y</td>
<td>&lt;.0001</td>
<td>0.2476</td>
<td>0.9750</td>
<td>NA</td>
</tr>
<tr>
<td>BE Workload Z</td>
<td>0.2901</td>
<td>0.6220</td>
<td>&lt;.0001</td>
<td>NA</td>
</tr>
<tr>
<td>NASA TLX Workload</td>
<td>0.0935</td>
<td>0.0029</td>
<td>0.7307</td>
<td>NA</td>
</tr>
<tr>
<td>Total Time</td>
<td>0.0006</td>
<td>0.0037</td>
<td>&lt;.0001</td>
<td>NA</td>
</tr>
<tr>
<td>Total Time Norm</td>
<td>0.0004</td>
<td>0.0027</td>
<td>0.0003</td>
<td>NA</td>
</tr>
<tr>
<td>Path Length</td>
<td>0.7053</td>
<td>0.0018</td>
<td>&lt;.0001</td>
<td>NA</td>
</tr>
<tr>
<td>Path Length Norm</td>
<td>0.7946</td>
<td>0.0008</td>
<td>&lt;.0001</td>
<td>NA</td>
</tr>
<tr>
<td>Avg. Velocity</td>
<td>&lt;.0001</td>
<td>0.1057</td>
<td>0.0105</td>
<td>NA</td>
</tr>
<tr>
<td>Std. Dev. Velocity</td>
<td>&lt;.0001</td>
<td>0.5405</td>
<td>&lt;.0001</td>
<td>NA</td>
</tr>
<tr>
<td>Avg. Force</td>
<td>&lt;.0001</td>
<td>0.5484</td>
<td>0.0137</td>
<td>NA</td>
</tr>
<tr>
<td>Std. Dev. Force</td>
<td>&lt;.0001</td>
<td>0.8240</td>
<td>0.0279</td>
<td>NA</td>
</tr>
<tr>
<td>Avg. Displacement</td>
<td>0.0018</td>
<td>0.6450</td>
<td>0.0536</td>
<td>NA</td>
</tr>
<tr>
<td>Std. Dev. Displacement</td>
<td>0.1863</td>
<td>0.1990</td>
<td>0.1271</td>
<td>NA</td>
</tr>
</tbody>
</table>

The analysis also considered the effect of possible interactions between factors. If an interaction between factors exists, then an interpretation of the main effects can lead to inaccurate results. There was no significant haptic*audio or audio*world interactions. Thus, the interpretations of the main effects due to haptic or audio and audio or world configurations is straightforward. There was one haptic*world interaction which will be discussed in Section 6.1.3. Also, the ordering of the runs was only significant with the NASA TLX workload measure. This makes sense since the NASA TLX is a subjective measure and could be easily biased by the change in the subjects perception of workload as the experiment progressed. Besides the NASA TLX workload measure, the effects of the factors and levels on the other measures are not influenced by run ordering or task learning.

Since almost every measure has a significant effect, as shown in Table 6.1, the results of each measure will be discussed in their own subsection. The five primary measures will be
presented in Section 6.1 followed by the secondary measures in Section 6.2. In the discussion of the results and when referring to haptic levels, no haptic feedback is designated as “N”, TTI algorithm as “T”, and VSODDS algorithm as “V”. When referring to the 3D audio levels, no audio feedback is designated as “N” and the DDGT algorithm as “D”. The two hard worlds are referenced as 1 and 2. The six haptic and 3D audio feedback combinations are designated as “NN” for no haptic and no audio feedback, “TN” for TTI with no audio feedback, “VN” for VSODDS with no audio feedback, “ND” for no haptic feedback with DDGT, “TD” for TTI with DDGT, and “VD” for VSODDS with DDGT. In the discussion, the difference between the means of two levels of a specific factor will often be presented. For example, N-T mean = 1.0313 specifies that the no haptic level mean minus the TTI haptic level mean is 1.0313.

### 6.1 Primary Measure Results

#### 6.1.1 Number of Collisions

In general, haptic force feedback reduced the number of collisions (p = 0.009). VSODDS significantly reduced the number of collisions as compared with no haptic feedback (see Table 6.2). There was no significant difference between TTI and the other haptic levels; however, TTI in general had fewer collisions than no haptic feedback (N-T mean = 1.0313). With regards to the number of collisions, VSODDS clearly outperformed both no haptic feedback and TTI by having fewer collisions on average and having a smaller variance as shown in Figure 6.1.

<table>
<thead>
<tr>
<th>Effect</th>
<th>Mean Diff</th>
<th>Std Error</th>
<th>P Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Haptic: N-V</td>
<td>3.1148</td>
<td>0.8089</td>
<td>0.0007</td>
</tr>
</tbody>
</table>

3D audio feedback did not reduce collisions but on average slightly increased the number of collisions (D-N mean = 1.0068). However, VSODDS combined with audio (VD) on average had fewer collisions than no haptics and no audio (NN) and also TTI with no audio (TD), as shown in
Figure 6.1: Boxplots (a) and mean with standard deviation plots (b) for number of collisions. 

Figure 6.1(b). This indicates that the DDGT audio feedback algorithm is not adversely increasing the number of collisions when combined with the VSODDS haptic algorithm.

### 6.1.2 Collision Length

Haptic feedback significantly reduced collision length ($p < .0001$). Both TTI and VSODDS haptic algorithms significantly decreased collision length over no haptic feedback (see table 6.3). VSODDS on average slightly reduced the collision length more than TTI (O-T mean = -0.3221) with approximately an 18.4% reduction in collision length.

<table>
<thead>
<tr>
<th>Effect</th>
<th>Mean Diff</th>
<th>Std Error</th>
<th>P Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Haptic: N-V</td>
<td>2.3422</td>
<td>0.4605</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Haptic: N-T</td>
<td>2.0201</td>
<td>0.4562</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>World: 1-2</td>
<td>-1.158</td>
<td>0.3749</td>
<td>0.0028</td>
</tr>
</tbody>
</table>

On average audio feedback increased the collision length (D-N mean = 0.2218), but this was not statistically significant. Audio alone (ND) increased the collision length but did not cause much change when combined with haptics (TD and VD), as seen in Figure 6.2. This suggests that audio when combined with haptic feedback is not helping nor hindering collision avoidance.
With regards to the different world environments, world 1 has a significantly smaller collision length than world 2 as shown in Table 6.3. This is reasonable since the minimum path length of world 2 is about 30% longer than world 1.

### 6.1.3 Behavioral Entropy X-Direction (forward/backward) Workload

With the behavioral entropy workload score for x-direction displacement of the haptic control stick (i.e. forward/backward motion of the quadrotor), there was a significant interaction between haptic feedback and world environment ($p = 0.0084$). The only significant difference in the interaction is between no haptic feedback on world 2 and VSODDS feedback on world 1 (see Table 6.4). This indicates that there is less workload with no haptic feedback on world 2 than there is with VSODDS on world 1.

### Table 6.4: Significant differences for behavioral entropy x-direction (forward/backward) workload.

<table>
<thead>
<tr>
<th>Effect</th>
<th>Mean Diff</th>
<th>Std Error</th>
<th>P Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Haptic*World: N2-V1</td>
<td>-0.08892</td>
<td>0.02639</td>
<td>0.0012</td>
</tr>
</tbody>
</table>

Also, there is a marginal significance between no haptics and VSODDS ($p = 0.0105$). However, since there is an interaction between haptics and world, it can be difficult to interpret...
the effect of the marginal significance. On average, TTI and VSODDS have a higher workload score than no haptics (see Figure 6.3(b)). Since the camera is fixed on the body x-axis of the quadrotor (i.e. camera faces in forward direction of quadrotor), operators might tend to trust the visual feedback more than the haptic feedback thus creating a higher workload due to haptics in that direction. Visual feedback is often more familiar to subjects and thus visual perception is more likely to dominate the other senses.

![Boxplots and mean with standard deviation plots](image)

Figure 6.3: Boxplots (a) and mean with standard deviation plots (b) for behavioral entropy x-direction (forward/backward) workload.

There is no significance due to audio feedback. On average, there was slightly more workload with audio feedback than without (D-N mean = 0.02891). Similar to haptic feedback, the correlation of increased workload due to audio feedback could be caused by the subjects trusting the visual feedback more than the audio. In addition, the 3D audio cues in the forward/backward directions are harder to differentiate between than for the left/right cues.

When considering the world factor, there is no significance. Again, however, the interaction between haptics and world makes it difficult to interpret the effect of the different worlds. Because this is the only measure with an interaction and since there is only one significant difference between all the haptic and world combinations, the effects of the haptic*world interaction is assumed to be negligible for the other measures.
6.1.4 Behavioral Entropy Y-Direction (left/right) Workload

There was a significant difference between haptic levels for the y-direction (i.e. side-to-side motion of quadrotor) behavioral entropy workload (p = <.0001). The TTI algorithm had significantly greater workload than both no haptic feedback and VSODDS, as shown in Table 6.5. This is not surprising since TTI is prone to major oscillations in tight spaces, particularly in the y, side to side, direction. The oscillation occurs because the TTI algorithm permits the haptic force to cause the control stick to overshoot the zero/neutral position. Thus, when approaching one side of a tight hallway, the force displayed by TTI causes the control stick to overshoot the neutral deflection which then commands a velocity towards the wall on the other side. The operator must overpower and over correct the haptic force to prevent unstable oscillations; this is a source of increased workload. An example of the unstable motion caused by TTI in narrow spaces is shown in Figure 6.4(a). This result also correlates with other research indicating that haptic force feedback often increases the workload [4, 5].

Table 6.5: Significant differences for behavioral entropy y-direction (left/right) workload.

<table>
<thead>
<tr>
<th>Effect</th>
<th>Mean Diff</th>
<th>Std Error</th>
<th>P Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Haptic: N-V</td>
<td>0.08457</td>
<td>0.02536</td>
<td>0.0038</td>
</tr>
<tr>
<td>Haptic: N-T</td>
<td>-0.09498</td>
<td>0.02512</td>
<td>0.0009</td>
</tr>
<tr>
<td>Haptic: V-T</td>
<td>-0.1796</td>
<td>0.02536</td>
<td>&lt;.0001</td>
</tr>
</tbody>
</table>

One key result of this thesis is that, while TTI increases y-direction workload, VSODDS significantly decreases it as compared with TTI and no haptic feedback (see Table 6.5 and Figure 6.5). This correlates with research indicating that some stiffness based haptic feedback can reduce workload over more traditional force feedback or no haptic feedback [39]. The significance of this result suggests that VSODDS helps the operator avoid collisions on the left and right of the quadrotor, both directions with very limited visual feedback. Essentially, VSODDS is decreasing the degree of freedom in the side-to-side direction which allows the operator to focus less on obstacles to the sides of the quadrotor. Because the force displayed by VSODDS will not cause the
control stick to overshoot the neutral position, oscillations in tight spaces do not occur. This allows the operator to more easily remain in the center of a narrow hallway as shown in Figure 6.4(b).

Figure 6.5: Boxplots (a) and mean with standard deviation plots (b) for behavioral entropy $y$-direction (left/right) workload.
There was no significance in \(y\)-direction workload due to 3D audio feedback or world environment (see Table 6.5). On average there was slightly more workload with audio feedback than without (D-N mean = 0.02064). Audio feedback was hypothesized to help reduce workload but it does not. However, these results also indicate that audio feedback is not adversely increasing the workload. On average world 1 had a slightly larger workload than world 2 (1-2 mean = 0.02064) which could indicate that world 1 is slightly harder than world 2.

### 6.1.5 Behavioral Entropy Z-Direction (up/down) Workload

In the \(z\)-direction (i.e. up and down motion of the quadrotor), there were no significant effects in behavioral entropy workload due to haptic feedback. On average, TTI and VSODDS slightly decreased the workload (see Figure 6.6). It is possible that there were not enough changes in the \(z\)-direction (up/down) throughout both worlds to excite a large enough difference to be significant. Also, even though humans live in a three dimensional world, we often still only concern ourselves with two dimensions. For instance, buildings are designed to minimize the need for changes in elevation. Thus a quadrotor flying through a building will more often then not be avoiding obstacles in the horizontal plane than in the vertical.

![Figure 6.6: Boxplots (a) and mean with standard deviation plots (b) for behavioral entropy \(z\)-direction (up/down) workload.](image-url)
There was also no significance due to audio feedback. On average, there was slightly more workload with audio feedback than without (D-N mean = 0.006761). Again, 3D audio feedback is not increasing or decreasing workload.

Table 6.6: Significant differences for behavioral entropy $z$-direction (up/down) workload.

<table>
<thead>
<tr>
<th>Effect</th>
<th>Mean Diff</th>
<th>Std Error</th>
<th>P Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>World: 1-2</td>
<td>-0.06262</td>
<td>0.01366</td>
<td>&lt;.0001</td>
</tr>
</tbody>
</table>

With respect to world environment, world 1 had a significantly smaller workload than world 2 (see Table 6.6). This is probably due to the fact that world 2 has more obstacles designed to induce more changes in the $z$-direction (up/down).

### 6.2 Secondary Measure Results

#### 6.2.1 NASA TLX Workload

For the NASA TLX workload measure, there were no significant differences between haptic feedback levels. On average TTI had a slightly higher workload score than no haptic feedback (N-T mean = -1.2417). Also, no haptics on average was higher than VSODDS (N-V mean 6.6060) as shown in Figure 6.7. Thus, in general, subjects considered VSODDS to contribute least to workload and TTI to contribute the most to workload. Since the NASA TLX workload measure is subjective and affected by run order, it is not meant to be used as a conclusive measure of workload. It is only included in order to provide a comparison with the behavioral entropy workload scores. The haptic feedback trends for the NASA TLX workload score are similar to the significance differences found with the $y$-direction behavioral entropy score.

Audio feedback did significantly contribute more to the NASA TLX workload than no audio feedback (see Table 6.7). This matches post-study responses by subjects who in general said they preferred no audio over audio feedback. It is important to remember that the more important objective measures such as behavioral entropy and collision length do not necessarily indicate an increase due to audio feedback. It is clear that audio feedback is not reducing workload but there
is not enough conclusive evidence to suggest that it increases it. Also, there was no significant
difference for the NASA TLX workload between world environments. On average world 1 had a
slightly smaller workload than world 2 (1-2 mean = -1.0693).

Table 6.7: Significant differences
for NASA TLX workload.

<table>
<thead>
<tr>
<th>Effect</th>
<th>Mean Diff</th>
<th>Std Error</th>
<th>P Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Audio: D-N</td>
<td>9.5363</td>
<td>3.0955</td>
<td>0.0029</td>
</tr>
</tbody>
</table>

Figure 6.7: Boxplots (a) and mean with standard deviation plots (b) for NASA TLX workload.

6.2.2 Total Time

Between the different haptic feedback levels there were significant differences in the total
time to complete the run (p = 0.0006). Runs using TTI took significantly more time than with no
haptic feedback and VSODDS (see Table 6.8). This makes sense since TTI on average displays a
higher force than no haptics and VSODDS, as shown in Figure 6.15(b). This means that on average
the haptic controller was displaced less in the x-direction for TTI (see Figure 6.8). Displacement
in the x-direction commands velocity in the forward direction of the quadrotor. Thus, less forward
displacement results in a smaller forward velocity and hence a longer completion time.
Table 6.8: Significant differences for total time.

<table>
<thead>
<tr>
<th>Effect</th>
<th>Mean Diff</th>
<th>Std Error</th>
<th>P Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Haptic: N-T</td>
<td>-23.0702</td>
<td>6.0207</td>
<td>0.0008</td>
</tr>
<tr>
<td>Haptic: V-T</td>
<td>-18.7895</td>
<td>6.0788</td>
<td>0.0078</td>
</tr>
<tr>
<td>Audio: D-N</td>
<td>14.8108</td>
<td>4.9473</td>
<td>0.0037</td>
</tr>
<tr>
<td>World: 1-2</td>
<td>-23.7811</td>
<td>4.9476</td>
<td>&lt;.0001</td>
</tr>
</tbody>
</table>

Figure 6.8: Average $x$-direction displacement of haptic control stick (i.e. direction that commands forward/backward quadrotor velocity).

Whereas TTI feedback increased the total run time, VSODDS did not significantly increase the time as compared with no haptic feedback (N-O mean = -4.2808) as shown in Figure 6.9. This means that the course can be completed just as fast with VSODDS as with no haptics but with significantly fewer collisions, as discussed in Section 6.1.1.

Audio feedback did significantly increase total time over no audio feedback (see Table 6.8). Either the audio was simply an annoying distraction that slowed the subjects down, or it made them more cautious. Even if the latter is true, the extra caution did not significantly reduce collisions due to the audio feedback. Thus, the slowing down caused by the audio was not beneficial. There was also a significant difference in total time for world environments. World 1 had a significantly
smaller total time than world 2 (see Table 6.3). Again, this makes sense because the minimum path length of world 2 is about 30% longer than world 1 and thus world 2 takes more time to complete.

6.2.3 Total Time Normalized

In order to compare the amount of time spent on both worlds, the total time measurement was normalized by the minimum path length of each world respectively (89 m for world 1 and 114 m for world 2). The significant effects due to haptics and audio are similar to those of total time not normalized. This can be observed by comparing Figures 6.9 and 6.10, and Tables 6.8 and 6.9. Thus, the haptic and audio results for total time are the same as discussed in Section 6.2.2.

Table 6.9: Significant differences for normalized total time.

<table>
<thead>
<tr>
<th>Effect</th>
<th>Mean Diff</th>
<th>Std Error</th>
<th>P Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Haptic: N-T</td>
<td>-0.2329</td>
<td>0.0585</td>
<td>0.0005</td>
</tr>
<tr>
<td>Haptic: V-T</td>
<td>-0.1836</td>
<td>0.05906</td>
<td>0.0074</td>
</tr>
<tr>
<td>Audio: D-N</td>
<td>0.1491</td>
<td>0.04807</td>
<td>0.0027</td>
</tr>
<tr>
<td>World: 1-2</td>
<td>0.1844</td>
<td>0.01807</td>
<td>0.0003</td>
</tr>
</tbody>
</table>

However, the significant effect due to the world environment is different for normalized total time than for total time. In the non normalized case, more time was spent on average on
world 2 (about 23.7811 seconds more as shown in the last row of Table 6.8). However, with the normalized case, more time per meter was spent on world 1 (about 0.1844 s/m more as shown in the last row of Table 6.9). This could suggest that world 1 is slightly more difficult than world 2 and thus more time per meter was spent on it.

### 6.2.4 Path Length

There was no significant difference in path length due to haptic feedback. On average TTI had a slightly greater path length than VSODDS (V-T mean = -1.6226) and no haptic feedback (N-T mean = -0.6894). TTI in general also had a greater variance in the data as shown in Figure 6.11. The greater path length and variance is likely due to the oscillations often caused by TTI in the narrow hallways as shown in Figure 6.4.

While there was no significance due to haptic feedback, 3D audio feedback did significantly increase path length as shown in Table 6.10. Since both total time and path length are greater when audio feedback is present, this suggests that audio feedback is more of a distraction than a help. However, the added distraction did not significantly increase collisions or workload. It is possible that the audio cues in general caused the subjects to overreact and thus oversteer when avoiding collisions, thereby increasing the time and path length without increasing the number of collisions.
In addition to audio feedback, there was a significant difference in path length between world levels. World 1 had a significantly smaller path length than world 2 (see Table 6.10). Again, this makes sense because the minimum path length of world 2 is about 30% longer than world 1.

### 6.2.5 Path Length Normalized

In order to better compare the path length on both worlds, the path length measurement was normalized by the minimum path length of each world respectively (89 m for world 1 and 114 m for world 2). Haptic feedback was not significant and the significance due to audio feedback is similar to that of path length not normalized. This can be observed by comparing Figures 6.11 and 6.12, and Tables 6.10 and 6.11. Thus, the haptic and audio results for path length normalized are the same as discussed in Section 6.2.4.

The significant effect due to the world environment is different for normalized path length than for path length. In the non normalized case, the path length is greater on average on world...
Table 6.11: Significant differences for normalized path length.

<table>
<thead>
<tr>
<th>Effect</th>
<th>Mean Diff</th>
<th>Std Error</th>
<th>P Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Audio: D-N</td>
<td>0.05657</td>
<td>0.01611</td>
<td>0.0008</td>
</tr>
<tr>
<td>World: 1-2</td>
<td>0.07057</td>
<td>0.01611</td>
<td>&lt;.0001</td>
</tr>
</tbody>
</table>

Figure 6.12: Boxplots (a) and mean with standard deviation plots (b) for total time normalized by world minimum path length.

2 (about 23.61 meters more as shown in the last row of Table 6.10). However, with the normalized case, the path length is greater on world 1 (about 0.07057 more as shown in the last row of table 6.11). Again, this could suggest that world 1 is slightly more difficult than world 2.

6.2.6 Average Velocity

When considering the quadrotor’s average velocity, TTI had a significantly lower average velocity than no haptics (see Table 6.12). The reasoning behind this is the same as discussed in Section 6.2.2; TTI displays a higher force on average which results in a smaller average velocity. VSODDS on average has a higher velocity than TTI (V-T mean = 0.06538) as shown in Figure 6.13. Therefore, VSODDS allows the operator to command a greater velocity and still maintain fewer collisions and less workload in the side-to-side direction.
Table 6.12: Significant differences for average velocity.

<table>
<thead>
<tr>
<th>Effect</th>
<th>Mean Diff</th>
<th>Std Error</th>
<th>P Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Haptic: N-T</td>
<td>0.1194</td>
<td>0.02318</td>
<td>&lt;.0001</td>
</tr>
</tbody>
</table>

Figure 6.13: Boxplots (a) and mean with standard deviation plots (b) for average velocity.

Both audio feedback and world environment factors did not have any significant differences. On average, audio feedback slightly reduced the average velocity (D-N mean = -0.03119). World 1 on average had a smaller average velocity than world 2 (1-2 mean = -0.05003).

6.2.7 Standard Deviation of Velocity

For the standard deviation of velocity, there were significant differences in the haptic levels (p = <.0001). Both no haptic feedback and VSODDS have a significantly greater standard deviation of velocity than TTI (see Table 6.13). Because TTI displays on average a higher force (see Figure 6.15), it restricts haptic displacement and thus also velocity. This causes there to be less variation in the velocity. See Figure 6.14 for the boxplots and mean plots for the standard deviation of velocity.

Audio feedback did not significantly increase or decrease the standard deviation of velocity; however, there was a significant difference due to world environment. On average, audio
Table 6.13: Significant differences for standard deviation of velocity.

<table>
<thead>
<tr>
<th>Effect</th>
<th>Mean Diff</th>
<th>Std Error</th>
<th>P Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Haptic: N-T</td>
<td>0.03855</td>
<td>0.009168</td>
<td>0.0002</td>
</tr>
<tr>
<td>Haptic: V-T</td>
<td>0.03746</td>
<td>0.009257</td>
<td>0.0004</td>
</tr>
<tr>
<td>World: 1-2</td>
<td>-0.03791</td>
<td>0.007534</td>
<td>&lt;.0001</td>
</tr>
</tbody>
</table>

Figure 6.14: Boxplots (a) and mean with standard deviation plots (b) for standard deviation of velocity.

feedback slightly increases the standard deviation (D-N mean = 0.004633). When considering the different worlds, world 1 had a significantly smaller standard deviation of velocity than world 2 (see Table 6.13). This could imply that subjects were more cautious on world 1, indicating again that world 1 might be more difficult.

6.2.8 Average Force

It was no surprise that no haptic feedback had a significantly lower average force than TTI and VSODDS as shown in Table 6.14 and Figure 6.15. The force for the no haptics level is not zero because there is a small centering force applied, as discussed in Section 5.4.2. TTI had a significantly higher force than VSODDS. This make sense when considering the math and nature behind each algorithm as discussed in Chapter 2. With VSODDS, it is possible to still reduce the
number of collisions while having a smaller average force. The smaller, less dominating force
could contribute to why most subjects in the post experiment questioning preferred VSODDS over
TTI.

Table 6.14: Significant differences
for average force.

<table>
<thead>
<tr>
<th>Effect</th>
<th>Mean Diff</th>
<th>Std Error</th>
<th>P Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Haptic: N-V</td>
<td>-0.5002</td>
<td>0.0577</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Haptic: N-T</td>
<td>-1.2352</td>
<td>0.05715</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Haptic: V-T</td>
<td>-0.735</td>
<td>0.0577</td>
<td>&lt;.0001</td>
</tr>
</tbody>
</table>

![Boxplots and mean with standard deviation plots for average force.](image)

Figure 6.15: Boxplots (a) and mean with standard deviation plots (b) for average force.

There were no significant differences for audio feedback or world environment. Audio
feedback slightly reduced the average force (D-N mean = -0.02832) when compared with no audio
feedback. On average, world 1 had a smaller average force (1-2 mean = -0.1186).

### 6.2.9 Standard Deviation of Force

There were significant differences in the standard deviation of force between the haptic
levels (p = <.0001). No haptic feedback had a significantly lower standard deviation of force than
TTI and VSODDS (see Table 6.15 and Figure 6.16). The centering force of no haptic feedback
is minimal and thus a small deviation is expected. Also, VSODDS had a significantly greater standard deviation of force than TTI. This makes sense because at times VSODDS will just have a small centering force and then at other times it will have a large resistive force to prevent a collision. The greater variation in force of VSODDS allows the operator to more easily perceive changes in the force magnitude. Since TTI has a larger average force and smaller variance, the changes are more muddled and not as effective as VSODDS.

<table>
<thead>
<tr>
<th>Effect</th>
<th>Mean Diff</th>
<th>Std Error</th>
<th>P Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Haptic: N-V</td>
<td>-0.6276</td>
<td>0.04009</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Haptic: N-T</td>
<td>-0.4657</td>
<td>0.03972</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Haptic: V-T</td>
<td>0.1619</td>
<td>0.04009</td>
<td>0.0004</td>
</tr>
</tbody>
</table>

Figure 6.16: Boxplots (a) and mean with standard deviation plots (b) for standard deviation of force.

Again, there were no significant differences for audio feedback or world environment. On average, audio feedback slightly increases the standard deviation (D-N mean = 0.007283) while world 1 had a smaller standard deviation than world 2 (1-2 mean = -0.07318).
### 6.2.10 Average Displacement

For the average displacement of the haptic controller, no haptic feedback had a significantly larger displacement than VSODDS (see Table 6.16). As shown in Figure 6.17, TTI also had a larger average displacement than VSODDS (V-T mean = -0.00137). The smaller average displacement for VSODDS is because when compared with TTI and no haptic feedback, it is less prone to cause over correction when avoiding obstacles. Again, VSODDS can be viewed as a haptic feedback algorithm that reduces the degree of freedom in the side-to-side direction, thus causing smaller average displacements of the control stick and smaller workload.

<table>
<thead>
<tr>
<th>Effect</th>
<th>Mean Diff</th>
<th>Std Error</th>
<th>P Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Haptic: N-V</td>
<td>0.00524</td>
<td>0.001472</td>
<td>0.0019</td>
</tr>
</tbody>
</table>

Table 6.16: Significant differences for average displacement.

![Figure 6.17: Boxplots (a) and mean with standard deviation plots (b) for average displacement.](image)

There is no significant effect on average displacement due to audio feedback. On average, audio feedback reduced the average displacement (D-N mean = -0.00055). Also, there is no significant difference between worlds. On average, world 1 had a smaller average displacement (1-2 mean = -0.00235).
6.2.11 Standard Deviation of Displacement

Standard deviation of displacement was the only measure without any significance for any of the factors (see Table 6.1). However, for completeness, the boxplots and means plots for the standard deviation of displacement are shown in Figure 6.18.

![Boxplots](image1.png)

Figure 6.18: Boxplots (a) and mean with standard deviation plots (b) for standard deviation of displacement.

6.3 Summary of Results

From the analysis of the experimental data, it can be concluded that, in general, haptic feedback helped improve operator performance while navigating a quadrotor UAV in a cluttered indoor environment. Haptic feedback reduced the number of collisions and the collision length. Operator workload was decreased in the side-to-side direction by VSODDS but was adversely increased by TTI. Overall, VSODDS clearly outperformed TTI and no haptic feedback. VSODDS significantly reduced the number of collisions and collision length without increasing the completion time nor decreasing velocity. It also displayed, on average, a smaller force than TTI, making VSODDS not overbearing yet distinctive enough to assist in avoiding collisions. Also, VSODDS significantly decreased operator workload by reducing the side-to-side degree of freedom. Due to these clear results, it is recommended that the VSODDS algorithm be used over TTI and no haptic feedback.
when piloting a quadrotor in indoor environments. Tables 6.17, 6.18, and 6.19 provide further comparisons of the results between the different haptic feedback levels.

Table 6.17: VSODDS vs. No Haptics: lists how VSODDS performed better (Pros), the same (Neutrals), and worse (Cons) than no haptics.

<table>
<thead>
<tr>
<th>Pros</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Fewer collisions and shorter collision length</td>
</tr>
<tr>
<td>• Lower behavioral entropy $y$-direction workload</td>
</tr>
<tr>
<td>• Lower NASA TLX workload (not significant)</td>
</tr>
<tr>
<td>• Moderately higher average force (larger but not too large to inhibit)</td>
</tr>
<tr>
<td>• Greater standard deviation of force (gives force greater distinction)</td>
</tr>
<tr>
<td>• Smaller average controller displacement (less over correction)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Neutrals</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Similar behavioral entropy $z$-direction workload (not significant)</td>
</tr>
<tr>
<td>• Similar total completion time</td>
</tr>
<tr>
<td>• Similar path length</td>
</tr>
<tr>
<td>• Similar average velocity and standard deviation of velocity</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Cons</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Slightly higher behavioral entropy $x$-direction workload (not significant)</td>
</tr>
</tbody>
</table>

Whereas haptic feedback helped operator performance, 3D audio feedback in most cases was neither helpful or harmful. However, audio feedback did significantly increase total completion time and path length. The increased time did not result in fewer collisions as would be hoped. The increased path length could be due to the audio feedback causing over corrections of the control stick when avoiding collisions. Also, 3D audio feedback significantly increased the NASA TLX workload score, which indicates that the subjects felt that audio feedback contributed to workload. However, audio feedback did not increase the behavioral entropy workload score in the $x$, $y$, or $z$ directions. It is possible that more audio feedback training could improve performance. After the experiment, many subjects stated that the audio feedback became more helpful once they got used to it and better understood how it worked. From these results, there is not enough conclusive evidence to reject or accept the effectiveness of 3D audio feedback in the tele-
Table 6.18: TTI vs. No Haptics: lists how TTI performed better (Pros), the same (Neutrals), and worse (Cons) than no haptics.

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
</table>
| **Pros**| • Fewer collisions (not significant)  
• Shorter collision length |
| **Neutrals** | • Similar behavioral entropy z-direction workload (not significant)  
• Similar path length  
• Smaller standard deviation of velocity. |
| **Cons** | • Slightly higher behavioral entropy x-direction workload (not significant)  
• Slightly higher behavioral NASA TLX workload  
• Longer total completion time  
• Smaller average velocity  
• Extremely higher average force (can inhibit performance)  
• Smaller variance in force  
• Prone to more over correction and oscillation in tight spaces |

operation of a UAV in indoor environments. Future work, such as discussed in Chapter 7, needs to be done in order to determine the effectiveness of 3D audio feedback.

With respect to world environment, there is very little evidence that the effects due to haptic or 3D audio feedback were different between the two hard worlds. This supports the idea that the results for haptic and audio feedback can be generalized for any world configuration. In future work, even more world configurations would be desirable to further generalize the results.

The hypothesis of the experiment was that visual feedback augmented with haptic and 3D audio feedback would reduce number of collisions and reduce operator workload while controlling a quadrotor in indoor environments. It is clear from the results that haptic feedback, VSODDS in particular, does improve operator performance and workload. However, 3D feedback does not improve operator performance nor workload as hypothesized.
Table 6.19: VSODDS vs. TTI: lists how VSODDS performed better (Pros), the same (Neutrals), and worse (Cons) than TTI.

<table>
<thead>
<tr>
<th>Pros</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Fewer collisions and shorter collision length (not significant)</td>
</tr>
<tr>
<td>• Lower behavioral entropy y-direction workload</td>
</tr>
<tr>
<td>• Lower NASA TLX workload (not significant)</td>
</tr>
<tr>
<td>• Shorter total completion time</td>
</tr>
<tr>
<td>• Larger average velocity (not significant)</td>
</tr>
<tr>
<td>• Larger standard deviation of velocity</td>
</tr>
<tr>
<td>• Smaller average force (not as overwhelming)</td>
</tr>
<tr>
<td>• Larger variance of force (gives force greater distinction)</td>
</tr>
<tr>
<td>• Smaller average displacement (not significant)</td>
</tr>
<tr>
<td>• Not prone to over correction and oscillations in tight spaces</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Neutrals</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Similar behavioral entropy z-direction workload (not significant)</td>
</tr>
<tr>
<td>• Similar path length</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Cons</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Slightly higher behavioral entropy x-direction workload (not significant)</td>
</tr>
</tbody>
</table>

6.4 Chapter Summary

This chapter discussed the results of the statistical analysis performed on the human subject experiment. Sections 6.1 and 6.2 discussed the results of the primary measure and secondary measures respectively. A summary of the results was provided in Section 6.3. Chapter 7 will provide concluding remarks and present possible future work.
CHAPTER 7. CONCLUSION

This thesis investigated the effectiveness of haptic and 3D audio feedback on operator performance and workload when operating a quadrotor in indoor environments. Three haptic force feedback and two 3D audio feedback algorithm were tested in human subject experiments. QuadSim, an indoor quadrotor simulation test bed was developed to study the effects of the multimodal feedback. Behavioral entropy was implemented to provide an objective measure of operator workload. This chapter reviews the contributions made by this thesis, summarizes the key results from the user study, and discusses areas of future work.

7.1 Contributions

Many contributions have been made by this thesis such as novel haptic feedback algorithms, implementation of 3D audio feedback, a robust and versatile simulation test bed, and demonstration of behavioral entropy as a measure of workload. These contributions are reviewed in the following sections.

7.1.1 Novel Haptic Feedback Algorithms

Many haptic feedback algorithms, such as TTI, have been developed to help pilot UAVs. This thesis adds two new haptic feedback algorithms: ODDS and VSODDS. These novel algorithms are based on the idea that springs are attached to the haptic controller in all direction. The stiffness of the spring dynamically changes in order to help avoid collisions. VSODDS is a derivative of ODDS and uses the velocity information of the UAV to scale the feedback force in order to provide greater sensitivity. From the pilot study, it was observed that the stiffness force displayed by ODDS can be too strong or too weak depending on the velocity of the UAV. VSODDS was designed to improve ODDS’ weaknesses and thus it was selected to be used in the human subject experiment. From the results of the experiment, VSODDS clearly outperformed both no haptic
and TTI feedback VSODDS by significantly improving operator performance and workload. Also, VSODDS did not suffer from oscillations and instability in tight spaces as was common with TTI. The experiment results of VSODDS are discussed further in Section 7.2.1.

An added benefit of ODDS and VSODDS is that they have several tunable parameters. This means that the haptic feedback can be customized to personal operator preferences or adapted for different world environments. Thus, improved performance could be gained on a operator-to-operator or world-to-world basis. Due to its features and experimental results, VSODDS is recommended as an effective haptic feedback algorithm to assist operators of UAVs in indoor environments.

### 7.1.2 Implementation of 3D Audio Feedback

Most previous research has focused on using visual and haptic feedback to improve UAV operator performance and workload. This thesis is unique by augmenting visual and haptic feedback with real-time 3D audio feedback. CDGT and DDGT are two novel algorithms that were developed to provide 3D audio warning cues to operators. To reduce sensory overload, these algorithms only play an alert cue in the direction of velocity and when within a threshold distance of an obstacle. CDGT uses a continuously sounding audio alert that increases in volume when approaching an obstacle. In the pilot study, it was observed that the graded, continuous sound was not distinctive enough to help gauge distances to obstacles. Therefore, DDGT was developed which uses a discrete audio cue that increases in frequency when approaching an obstacle. DDGT was used in the human subject experiment and performed better than CDGT. However, the results from the experiment suggest that in general 3D audio feedback does not help nor harm operator performance or workload. Even though the results are not significant and more work is needed, this thesis demonstrates that 3D audio feedback is another feasible modality to explore in improving the performance of teleoperation. A review of DDGT’s experimental results is given in Section 7.2.2.

### 7.1.3 Improved Simulation Test Bed

For this type of research, it is important to have a good test bed for experimentation. This thesis contributes QuadSim, a robust and versatile indoor quadrotor simulator. QuadSim is able
to display visual, haptic, and 3D audio feedback in three dimensions. Realistic quadrotor motion and dynamics is displayed in the simulator by using MATLAB/Simulink to solve the quadrotor’s complex equations of motion. The realism of the simulator is further enhanced by the use of OpenGL graphics to draw the indoor environments.

QuadSim can easily be modified to be used with future research. New indoor environments can quickly be made using XML code. Simulation, quadrotor, haptic, and 3D audio settings can be modified. New haptic and 3D audio algorithms can be added and tested. Also, simulation experiments, a set of runs and transition, can easily be created in order to facilitate testing and experimentation. This feature proved to be very useful and time saving when performing the human subject experiment. All of these and other features makes QuadSim a valuable research tool.

7.1.4 Implementation of Behavioral Entropy

In order to measure operator workload, many researchers have used subjective measures such as the NASA TLX. Subjective measures suffer from subject bias or preconceptions and even task ordering as found in this thesis’ human subject experiment. Instead of relying on a subjective measure, this thesis used experiment data to objectively measure workload using behavioral entropy. Using the haptic controller deflection data for a subject’s unloaded baseline run, a model was created to predict future displacements. The error between the actual and predicted displacements was used to quantify the workload.

Since behavioral entropy uses the experiment data, it is not biased by the subjects perception and is also non invasive. Another benefit of behavioral entropy is that segments of the data can be used calculate the workload over a specific time interval of the task. Most other workload measures only provide an overall workload score for a task. Even though this thesis focused on an overall workload score for each run in the experiment, the ability to examine the workload over a specific time span or area could be useful. An example of this is shown in Figure 7.1, where world 2 has been segmented into 10 sections with the behavioral workload calculated for each section. The workload scores and quadrotor paths are from runs TN and VN respectively for Subject 1 from the user study.
Figure 7.1: Quadrotor path on world 2 with $x$, $y$, and $z$ behavioral entropy workload scores for Subject 1 on (a) run TN and (b) run VN.
This feature could be useful for determining which obstacles are more difficult or how the haptic feedback affects workload over different sections for different algorithms. It could also be used to design new haptic or 3D audio feedback algorithms that are more effective in reducing workloads for certain types of obstacles. For example, in Figure 7.1, the section with the highest y-direction behavioral entropy workload for both runs is the section with wind blowing the quadrotor to the side. As would be expected, the wind is increasing the operator workload. The segmentation of behavioral entropy workload is discussed further in Section 7.2.

7.2 Human Subject Experiment

Many significant results were obtained from the human subject experiment. The following sections review the key results pertaining to haptic feedback, 3D audio feedback, and world environment. Additional insights are also discussed.

7.2.1 Haptic Feedback

It was hypothesized that haptic feedback would decrease the number of collisions and reduce the operator’s workload. When considering collisions, both TTI and VSODDS did significantly decrease the collision length over no haptic feedback. VSODDS also significantly decreased the number of collisions and TTI on average had fewer collisions than no haptics. The results for TTI are consistent with work previously done [3].

When considering operator workload, there was mixed results for haptic feedback. In the haptic controller x-direction (forward/backward quadrotor motion), TTI and VSODDS slightly increased the behavioral entropy workload over no haptic feedback. It is possible that since the camera is aligned in the haptic controller x-direction, the operators trusted visual feedback more than haptic feedback. If additional training time was allotted, operators could become more familiar with haptic feedback thus reducing the dependence on visual feedback and possibly reducing workload in the direction of the camera. In the haptic controller z-direction (up/down quadrotor motion), TTI and VSODDS feedback slightly decreased workload. Possible reasons for no significant workload results in the z-directions are discussed in Section 7.2.3.
While there was no significant workload results in the $x$ or $z$ directions, there was in the $y$-direction (side-to-side quadrotor motion). TTI significantly increased the $y$-direction workload while VSODDS significantly decreased it. The nature of TTI to oscillate in narrow spaces is likely a factor in its increased workload score. VSODDS, however, does not suffer from the oscillations and is better at helping the operator stay in the center of a narrow space. Essentially, VSODDS is reducing the degree of freedom in the side-to-side direction and thus decreasing the workload in that direction. Further evidence of this behavior can be observed from comparing the two algorithm’s workload scores over different sections of the world environment as discussed in Section 7.1.4. Table 7.1 shows the average behavioral entropy workload scores for TTI and VSODDS for each of the 10 sections as shown in Figure 7.1. These scores are average workloads for all the subjects who had TTI and VSODDS haptic feedback combined with no audio feedback runs (TN and VN) on world 2. It is clear that VSODDS on average had lower $y$-direction workload scores than TTI in almost every section. Additional comparisons of the sectional workload scores could be done to further illustrate how the behavioral entropy workload changes between haptic levels which is left as future work.

Table 7.1: Sectional behavioral entropy workload scores for runs TN and VN on world 2.

<table>
<thead>
<tr>
<th>Section</th>
<th>TN2</th>
<th>VN2</th>
<th>Section</th>
<th>TN2</th>
<th>VN2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$x = 0.360$</td>
<td>$y = 0.425$</td>
<td>$z = 0.157$</td>
<td>$x = 0.403$</td>
<td>$y = 0.280$</td>
</tr>
<tr>
<td>1</td>
<td>$x = 0.521$</td>
<td>$y = 0.594$</td>
<td>$z = 0.214$</td>
<td>$x = 0.494$</td>
<td>$y = 0.319$</td>
</tr>
<tr>
<td>2</td>
<td>$x = 0.435$</td>
<td>$y = 0.547$</td>
<td>$z = 0.267$</td>
<td>$x = 0.493$</td>
<td>$y = 0.339$</td>
</tr>
<tr>
<td>3</td>
<td>$x = 0.436$</td>
<td>$y = 0.540$</td>
<td>$z = 0.499$</td>
<td>$x = 0.484$</td>
<td>$y = 0.311$</td>
</tr>
<tr>
<td>4</td>
<td>$x = 0.342$</td>
<td>$y = 0.183$</td>
<td>$z = 0.511$</td>
<td>$x = 0.369$</td>
<td>$y = 0.230$</td>
</tr>
</tbody>
</table>
From the experiment results, it is concluded that the VSODDS haptic feedback algorithm is the most useful for improving operator performance and workload. VSODDS reduces collisions while not increasing time nor decreasing velocity. It also displays on average a smaller force than TTI that is not overbearing while being distinctive enough in avoiding collisions. Overall it decreases workload by reducing the side-to-side degree of freedom.

7.2.2 3D Audio Feedback

It was also hypothesized that 3D audio feedback would reduce the number of collisions and operator workload. Unlike haptic feedback, the experimental results for 3D audio feedback do not confirm the hypothesis. The DDGT audio algorithm used in the experiment neither decreased or increased the number of collisions. It also did not improve or worsen the operator’s workload as measured by behavioral entropy. From post experiment questioning, many subjects felt that the 3D audio feedback was not as intuitive as the visual or haptic feedback and was frustrating at times. This matches with the NASA TLX workload being significantly greater for audio feedback. However, many subjects also felt that the audio feedback became more helpful as they got used to it. It is possible that additional and better training with the 3D audio feedback could make it more effective.

One reason 3D audio feedback was included as an additional modality in this thesis, was to counteract VSODDS’ major weakness. VSODDS will only display a force when the haptic controller is displaced; therefore, warning forces are not displayed due to potential collisions caused by external forces such as wind. In situations with wind blowing the quadrotor towards an obstacle, an audio alert cue will still provide a warning even if the haptic feedback does not. Even though in general 3D audio did not improve operator performance and workload, there is some evidence that it did help in windy situations. When considering just section 7 of world 2 (see Figure 7.1), a section with 0.75 m/s wind (obstacle 5 in Figure 5.3), VSODDS combined with DDGT on average reduced collision length and workload over VSODDS with no audio feedback as shown in Table 7.2.

From these results, it is clear that more work is needed in order to fully accept or reject the usefulness of 3D audio feedback. New algorithms that are more intuitive to users could be created. Another idea is to create an algorithm that only gives a 3D audio alert cue when the haptic con-
Table 7.2: Average collision length and behavioral entropy workload for runs VN and VD in section 7 of world 2.

<table>
<thead>
<tr>
<th>Measure</th>
<th>VN2</th>
<th>VD2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Collision Length</td>
<td>1.404</td>
<td>1.069</td>
</tr>
<tr>
<td>BE Workload</td>
<td>x = 0.594</td>
<td>x = 0.538</td>
</tr>
<tr>
<td></td>
<td>y = 0.574</td>
<td>y = 0.496</td>
</tr>
<tr>
<td></td>
<td>z = 0.274</td>
<td>z = 0.226</td>
</tr>
</tbody>
</table>

Controller is not displaced and an external force is moving the UAV towards an obstacle. This would help counter the weakness of stiffness feedback algorithms like VODDS without overloading the operator senses. Many improvements could be done in order to make 3D audio feedback more effective.

### 7.2.3 World Environment

From the results of the experiment, there was little evidence that the significant effects due to haptic or 3D audio feedback were different between the worlds. This indicates that haptic feedback would improve operator performance and workload for other indoor environments. However, to further generalize the effectiveness of multimodal feedback, more world environments need to be tested.

Based on what was learned from this thesis, a few improvements could be made in the development of future worlds. First, adding wind to the world is probably not necessary. In most indoor environments, wind is not usually present or as strong as the wind sections in this thesis. Even if there was wind due to air conditioning or an open window, advanced autopilot control laws can be developed to reject external disturbances. The wind in the human subject proved to make navigating the obstacle course harder than it needed to be. Second, the new world environments could provide more changes in elevation. It is likely that there were not enough elevation changes in the two hard worlds to sufficiently show significant difference in the $z$-direction behavioral entropy workload. Even though it is natural to minimize elevation changes in flight, it is still important to fully examine how multimodal feedback can improve performance in the vertical direction. Lastly,
many indoor environments do not just contain static obstacles. Dynamic obstacles such as humans, animals or falling debris are likely to be present in many environments. Thus, it would beneficial to develop new worlds with dynamic obstacles in order to examine how haptic and audio feedback react. Including these and other features in indoor environments for future studies would further genealize the results and effectiveness of multimodal feedback as discussed in this thesis.

7.3 Future Work

This thesis has only explored the effectiveness of a few different haptic and 3D audio feedback algorithms on operator performance and workload in two indoor environments. Additional work is needed in many areas such as haptic and audio algorithms, world environments, experiments, simulation, and hardware. Future work could include:

- Develop new or improve current haptic feedback algorithms. It is likely that there are other haptic algorithms that could be developed to perform better than VSODDS. One example might be to use vibrotactile feedback instead of force or stiffness feedback. Vibrations could be added to VSODDS to warn the operator of potential collisions due to an external force.

- Develop new or improve current 3D audio feedback algorithms. It is easy to overload the senses with audio feedback and thus algorithms with minimal feedback could be developed. For example and as discussed in Section 7.2.2, 3D audio cues could only be displayed in certain situations such as when an external force is moving the vehicle. Also, different audio sounds could be explored. It is possible that the sound must be sufficiently rich in order for the operator to distinguish the location the sound. Certain sounds also might be less annoying than others.

- Investigate the segmentation of behavioral entropy workload. As discussed in Section 7.1.4, a workload score can be calculated for specific world segments or time intervals. More in depth investigation than presented in this chapter could be done to explore how operator workload changes through out the world environments. This could be very useful in examining how the multimodal feedback algorithms affect workload for different obstacles. The information gained from such an investigation could also help in the development of new haptic or 3D audio algorithms.
• Improve the prediction model in the behavioral entropy workload calculation. This thesis used previous haptic controller displacements to predict future displacements. A potential problem with this is that haptic feedback is directly influencing the haptic controller behavior. This might mean that the workload score does not entirely reflect the operator’s workload because the haptic controller motion is not entirely caused by the operator. Part of the workload score could be due to workload imposed by the haptic feedback algorithm. Future work needs to be done to investigate if this is a problem or not.

• Develop new indoor world environments. The types of obstacles and challenges vary greatly between indoor environments. For example, navigating in a warehouse is much different from navigating a collapsed building after an earthquake. Specific environments could be created for certain indoor applications or multiple environments could be tested to further generalize the effects of multimodal feedback as discussed in Section 7.2.3.

• Perform user studies to tune haptic and audio algorithm parameters. The effectiveness of multimodal feedback could be improved by better tuning of the parameters. A user study could be performed to identify a set of parameters that provides optimal performances for a general population of operators.

• Perform user studies with algorithm parameters tuned to operator preference or based on the world environment. Since no two people are the same, operators have different preferences on how the force or audio feedback should feel or sound. Also, every world environment is different and thus certain parameters could be more suitable. Overall operator performance could improve by using operator-to-operator or world-to-world customized parameters. The additional training required to customize the parameters could also improve operator performance.

• Simulate a laser range finder or add additional range measurements. QuadSim only finds distances to obstacles in 6 directions relative to the quadrotor body frame: forward, backward, left, right, up, and down. Thus small obstacles or obstacles aligned at certain angles can go undetected and no haptic or audio feedback cues would be displayed. QuadSim could be improved by including additional range measurements or simulating a laser range finder.
• Improve realism of indoor environments. QuadSim does provide realistic graphics; however, the realism could be further improved by using advanced lighting, shading, and texture mapping. An even higher fidelity simulation will help bridge the gap between simulation and physical implementation.

• Implement the haptic and 3D audio feedback in hardware. This thesis has only focused on simulation; however, hardware testing is needed to validate the results from simulation. To do so, BYU's MAGICC Lab motion analysis room, which utilizes several infrared cameras to track positions and velocities of objects, could be used. A real quadrotor could be piloted in the room with the assistance of the multimodal simulator. QuadSim could provide a virtual camera view of the room with virtual objects contained therein as shown in Figure 7.2. The quadrotors state information obtained from the motion analysis cameras could be fed to the simulator instead of the states calculated by MATLAB to update the graphic animation, thereby providing real quadrotor motion in a real environment. A DLL would need to be created in order for the motion analysis cameras to communicate with QuadSim and the PHANTOM with the physical quadrotor.

Figure 7.2: BYU’s Motion Analysis Room with infrared cameras (left) and the simulation view of the room (right).
REFERENCES


