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Towards Presence in Telerobotics: Real-time Image Abstraction for Virtual Reality

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Abstract

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The application of Virtual Reality (VR) to telerobotics is a current area of study due to a desire for the increased spacial awareness VR provides. However, attempts to implement such a system using standard teleoperation techniques result in sub-par performance and an uncomfortable experience for the user; the benefits of a VR based system are entirely eliminated. The system proposed by this project incorporates elements of data abstraction to produce abstractions of the environment. This process reduces the performance requirements of providing the user presence within the telerobot's space such that reasonable spacial awareness can be achieved.

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Chapter 1

Introduction

The desire for a feeling of presence [1] within a space that is not your own is one that drives much technological innovation. Whether it be within a virtual space such as in video games or simulation training [2], or within a different real world location as in telerobotics, greater presence allows the user to more naturally and intuitively interact with the presented environment as if they were truly there. In telerobotics in particular, where the aim can often be to interact with very dangerous or industrial environments, intuitive control is essential to safe and effective operation.

Virtual Reality (VR) is a technology spearheaded by the video games industry for use in immersive gaming application. Through the use of a tracked headset, giving the user the ability to freely look around a 3D space, it provides unparalleled presence within a virtual world- comparable to presence within a real, physical space [3, 4]. To be able to incorporate VR into teleoperation is therefore desirable, however, sending a video feed to the headset as if it were a normal monitor has been found to lead to motion sickness [5]. This is due to VR's high frame rate and low latency requirements. It's widely accepted that for a VR application to not cause motion sickness and headaches due to frame rate, it must maintain at least 90 frames per second (fps) [6]; a minimum of 60 fps can also be acceptable [7], but generally only for applications with little motion or when used by people with lower susceptibility to motion sickness. Unfortunately, to transmit 90 fps from a stereo camera rig (two images are required to perceive 3D) to the computer running the VR application has

bandwidth requirements too high to be currently implementable outside the most expensive of designs.

Another consideration is the ability to look around the space independently, as this is a major factor in providing presence to the user in VR. This can be achieved by mounting the stereo camera rig on a gimbal, however to build a gimbal that is able to track the angle of the user's head accurately and with low latency is, once again, expensive and challenging [8]; if not implemented perfectly the user would experience significant sickness and dissociation from the space.

The aim of this project is to design and implement a VR based teleoperation system that utilises data abstraction to minimise the outlined technical issues, providing the foundations for future systems with the ability to provide true presence to the user. To achieve this, each image is reduced down to its most essential features, reducing its size and therefore the required bandwidth significantly. Each image pair must then be transmitted to a server and combined into a single 3D model of the space that could be looked around freely through the VR headset. As the camera feed is converted to a 3D model rather than displayed directly as images, the headset could run at its maximum frame rate of 90fps even if the model is updating at a much slower rate.

The system (outlined in Figure 1.1) consists of 2 platforms- a server that runs a VR environment and reads user input from an Xbox 360 controller, and a rover platform that is controlled from said environment and supplies the abstracted images that the 3D model in the environment is built from. The rover (Figure 1.2) is a simple drivable platform with a stereo camera gimbal mounted on it (adapted from one produced by previous students [9]), and is the subject of Chapter 5. The server is a powerful PC running Windows 10 [10] and a HTC Vive [11]. The design of the program the server runs is the subject of Chapter 6. The data abstraction algorithm the system uses is novel, so its design and development is initially discussed in isolation in Chapter 4 and then its application within the system addressed in Chapter 5. The full system will be evaluated in Chapter 7.

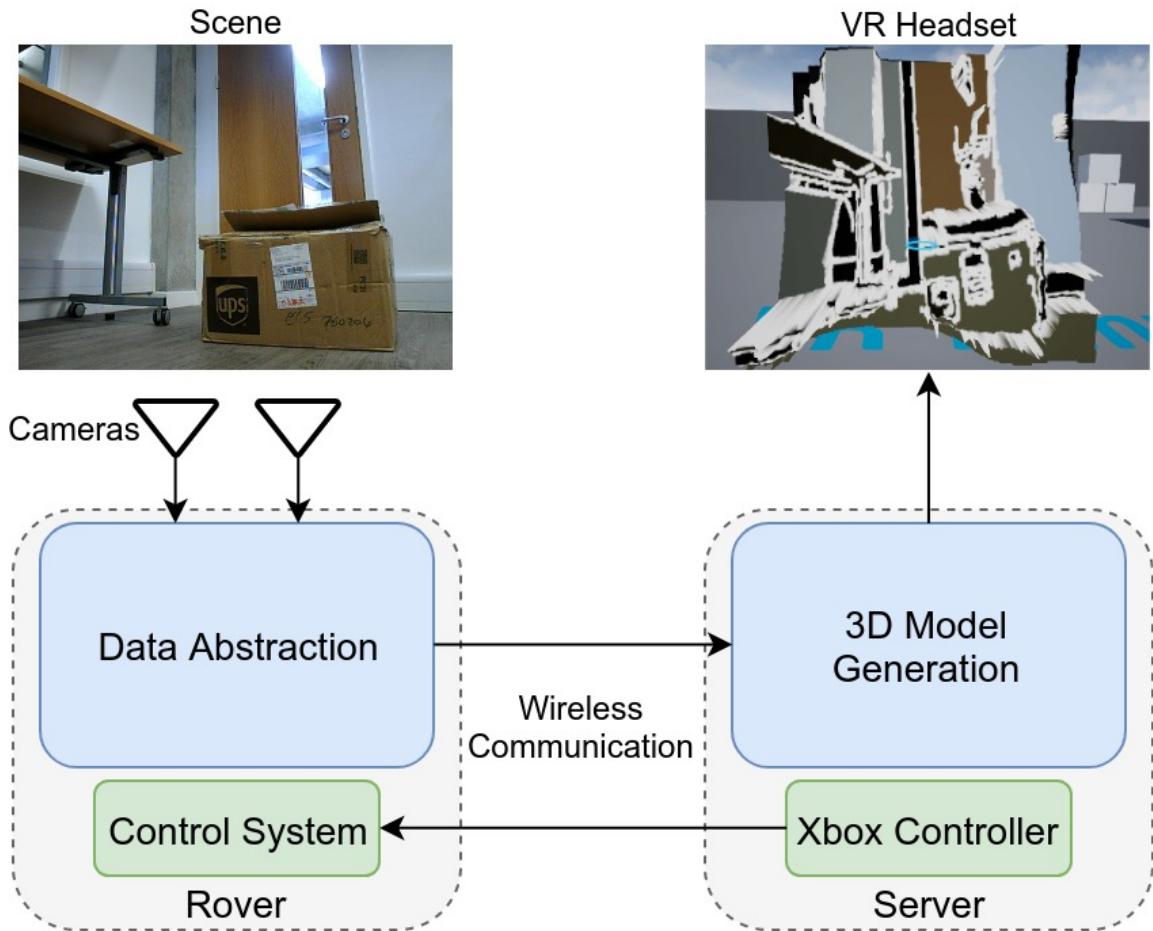


FIGURE 1.1: System Outline. It can be seen that the scene the rover's cameras are observing (top left) is within the VR environment (top right) as a simple abstracted 3D representation.

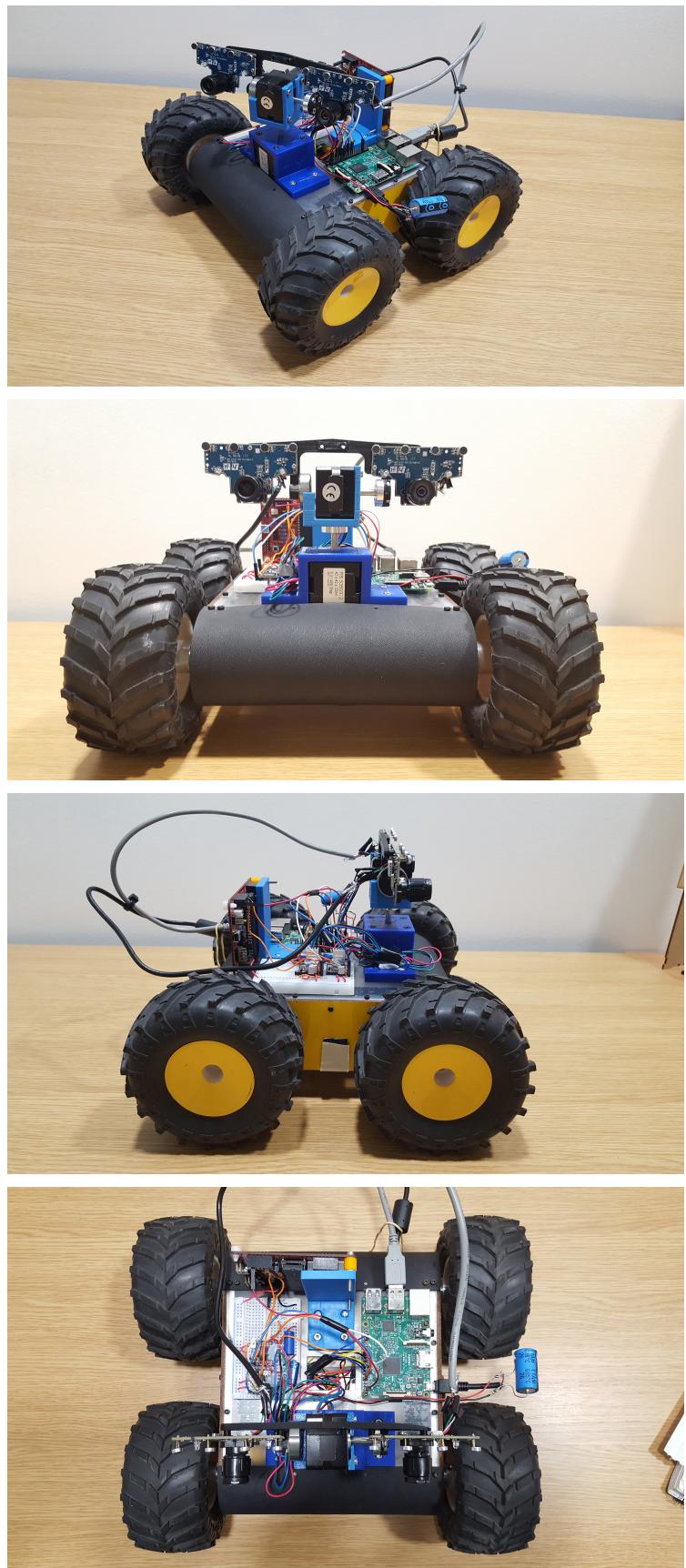


FIGURE 1.2: Rover Pictures.

Chapter 2

Background

2.1 Virtual Reality

The term Virtual Reality (VR) refers to the generation of a 3D environment that can be interacted with by a user in a realistic fashion, with the aim of immersing the user in the environment as if it were the real world [12]. While there are a large array of systems that can be considered VR, whenever the term is used in this report it is only referring to the head-mounted display (HMD) systems that have become popular in recent years with the release of the Oculus Rift [13] and the HTC Vive [11] (Figure 2.1). These are both consumer grade systems that are aimed at the immersive gaming market.



FIGURE 2.1: HTC Vive. Pictures of the Vive headset, reproduced from [11].

HMD based systems display different images for each eye to provide the user with a sense of depth within the 3D environment, making the headset effectively operate like a pair of binoculars into the virtual world. The headset is also tracked in 3D space, and this movement translated into the 3D environment with very low latency. These features, among others, are all implemented with the aim of providing the user with presence within the virtual space that is comparable to observing the real world.

Due to its availability at the University of Southampton and in my own home, the HTC Vive was used as the VR device in the development and implementation of the teleoperations system discussed in this report.

2.2 Telerobotics

A telerobot is a robot controlled from a distance by a human operator [14]. Telerobots are typically developed to undertake activities within environments that are too dangerous or costly for humans to work in. Typical fields of telerobotics research include deep-space exploration [15], deep-sea exploration [16], and handling radioactive materials [17].

2.2.1 VR in Telerobotics

The use of HMDs in teleoperations is not a new concept; NASA's Robonaut 2 was sent to the International Space Station in 2011 and can be controlled through a headset that displays the output of the robot's head cameras [18], and flying drones by First Person View (FPV), an analogue video feed transmitted over radio to a HMD, has become very popular in recent years [19]. However, these systems are either incredibly expensive (Robonaut 2 is worth millions of dollars) or very limited (FPV systems are only capable of sending one low quality video stream over a short distance), and all suffer from the motion sickness issues discussed in Chapter 1. While stereo camera FPV systems have been developed, so the user has depth perception and better presence in the drone's view, the motion sickness problem remains the major drawback of HMD based teleoperations systems [20].

As previously established, motion sickness in VR is mitigated through high frame rates and low latency. However, typically VR based teleoperations systems are direct VR systems, so they display the video feeds provided by the telerobot's cameras directly in the headset. This entirely ties the frame rate and latency of the headset to the capabilities of the video transmission system, and only the most expensive and complicated systems will meet the strict requirements for comfortable VR and the spacial presence desired.

An alternate option to a direct system is an indirect system. This is one in which the video feed is abstracted from the headset in some way in the hope of providing improved comfort and awareness. Indirect systems can come in a variety of forms, such as placing the video feed on a virtual screen in the VR environment and controlling the robot using virtual controls laid out in front of the screen [21], or a 3D map generated from a multi-line LiDAR and IMU [22] (Figure 2.2). These examples show the potential of indirect systems as a solution to VR based teleoperations, however neither of them provide true presence within their respective robots' environments. This project aims to contribute to this field of research by demonstrating an alternate approach to the problem that is capable of providing greater presence than these previous attempts.

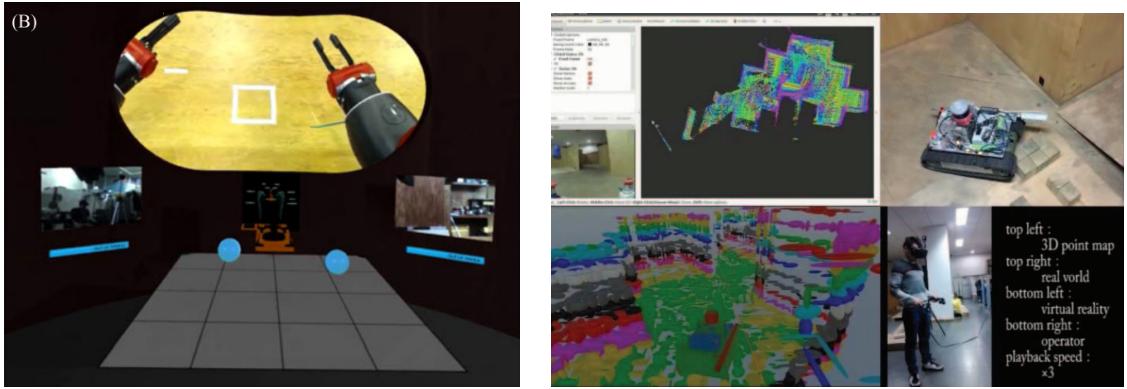


FIGURE 2.2: Indirect VR teleoperations examples. A virtual control room based system (left) and a LiDAR 3D map based system (right), reproduced from [21] and [22].

2.3 Data Abstraction

Data abstraction is the phrase that will be used in this report to describe the act of reducing an image down to only its most essential elements. It is similar in concept to an artist sketching a scene instead of attempting a full drawing. Comparing the concept to data compression is apt, as both aim to reduce the file size of the image, however data abstraction takes a very different approach to solving the problem than standard compression algorithms.

Data compression is the storing of information using a more space efficient encoding [23]. While some information is lost during lossy compression, the aim regardless of the algorithm used is to retain as much of the original information as possible. In contrast, the aim when utilising data abstraction is to discard all the information that is unnecessary to fulfilling the image's specific purpose. For example, if all that is required of an image is that basic shapes can be identified, then only the information on the boundaries of the shapes is necessary; the rest of the image can be discarded. An implementation of data abstraction can be seen in Figure 2.3.

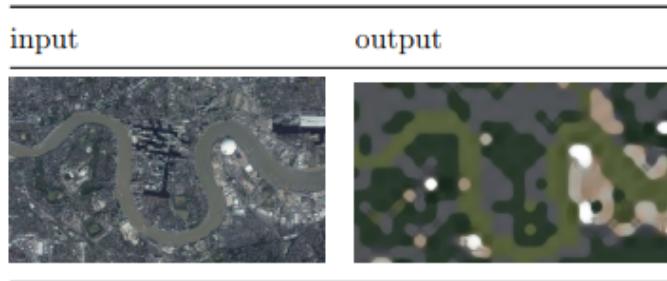


FIGURE 2.3: Data Abstraction Example. This is an abstraction of an aerial photograph of London, reproduced from [24].

2.4 Sobol Sequences

Sobol sequences are quasi-random sequences that were introduced to aid in approximating integrals. The aim is to form a sequence of points that are evenly spread across an S-dimensional unit cube [25], providing a much more even spread of points across the chosen space than can be produced from a pseudo-random number source

(Figure 2.4). The code used in this project to produce these sequences was created by Leonhard Grünschloß [26].

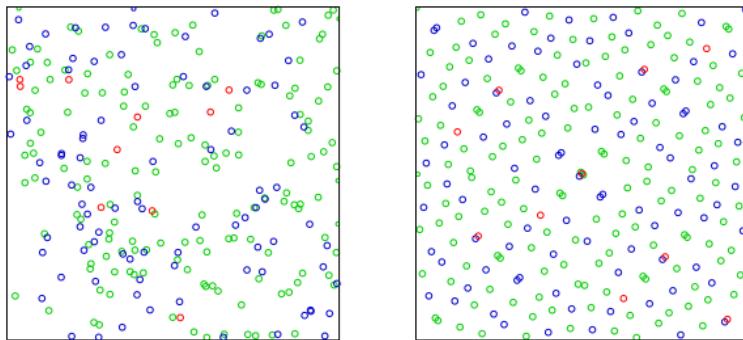


FIGURE 2.4: Comparison of pseudo-random and quasi-random sequences. 256 points from a pseudo-random generator (left) and 256 points from a Sobol sequence (right), reproduced from [27].

2.5 Computer Vision

Computer vision is the automatic analysis of images and extraction of the useful information they contain [28]. A raw image is simply a large matrix of colour values, so for a computer to take action based on the contents of an image it must be able to recognise features using analysis of this data. Doing so involves many different techniques such as statistical pattern classification and geometric modelling [29]. All computer vision methods in this project are implemented using the OpenCV libraries, and the example programs provided with them used as starting points for development [30].

2.5.1 Edge Detection

When attempting to recognise the features of an image, knowing the locations of the edges of objects within the scene is often very useful. An edge is defined as a significant local change in intensity, usually due to a discontinuity in either the intensity or its first derivative [31]. There are many algorithms available that will detect the edges of an image from the locations of these discontinuities. When the

most popular algorithms (Laplacian of Gaussian, Robert, Prewitt, Sobel, and Canny) are compared [32], the most effective in almost all scenarios is Canny edge detection [33], therefore this is the algorithm utilised in this project. Canny edge detection is demonstrated in Figure 2.5.

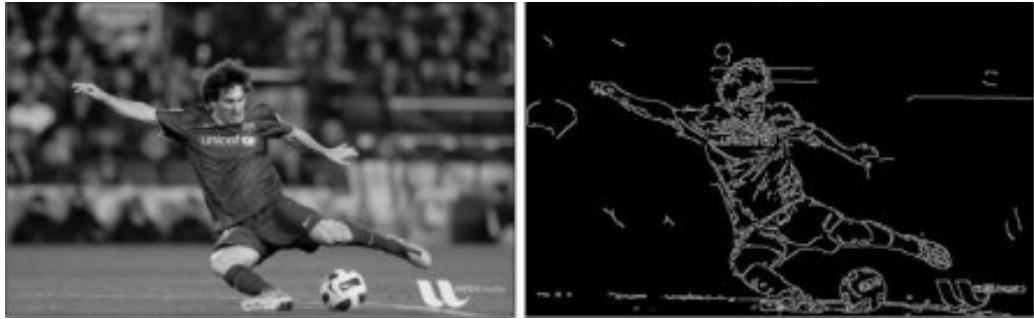


FIGURE 2.5: Canny Edge Detection Example. Simple edge detection program applied to a fairly detailed photo of Lionel Messi, to demonstrate its effectiveness with even complex images. Figure taken from an OpenCV Canny tutorial [34].

2.5.2 Flood Filling

Flood fill algorithms determine the area connected to a given cell (the seed point) in a multi-dimensional array that have similar intensity values for the purpose of filling them with a chosen colour [35]. This is a technique that is not only useful in image processing, but also for many other fields such as in passive acoustic monitoring, where finding the area connected to a given node can be useful as part of tracking in 4D space (x,y,z,time) [36]. A demonstration of flood fill has been presented in Figure 2.6.

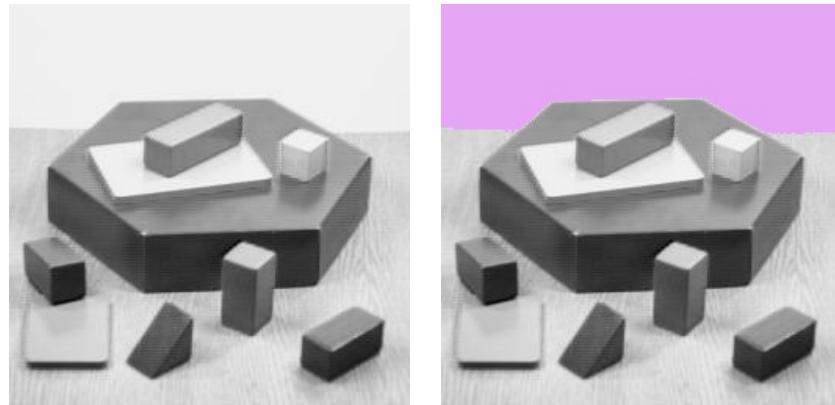


FIGURE 2.6: Flood Filling Example. The original image (left) was provided by OpenCV [30]. The right image is the result of flood filling from the top left corner.

2.5.3 Depth Mapping

The main component in the human brain’s perception of 3D is the identification of disparity between the locations of objects in the 2D images being produced by our eyes [37]. The greater the difference in the horizontal placement of an object between the images, the closer the object to the observer. This technique can be used in computer vision to produce depth/disparity maps. Depth maps display differences in depth as a gradient from white to black (Figure 2.7), and can be produced using a variety of different algorithms. The most common are block matching algorithms, which use simple geometry and the matching of blocks of pixels horizontally in the 2 images to calculate depth [38]. For these algorithms to locate the same object in different places in the 2 images, the cameras taking them must be calibrated to rectify any distortion due to the lenses [39] or discrepancies in the mounting that would cause them to be out of line [40]. Without this image rectification, the similar blocks the algorithm is attempting to locate will not be on the same horizontal row or will be distorted, so the algorithm will produce a mostly black image.

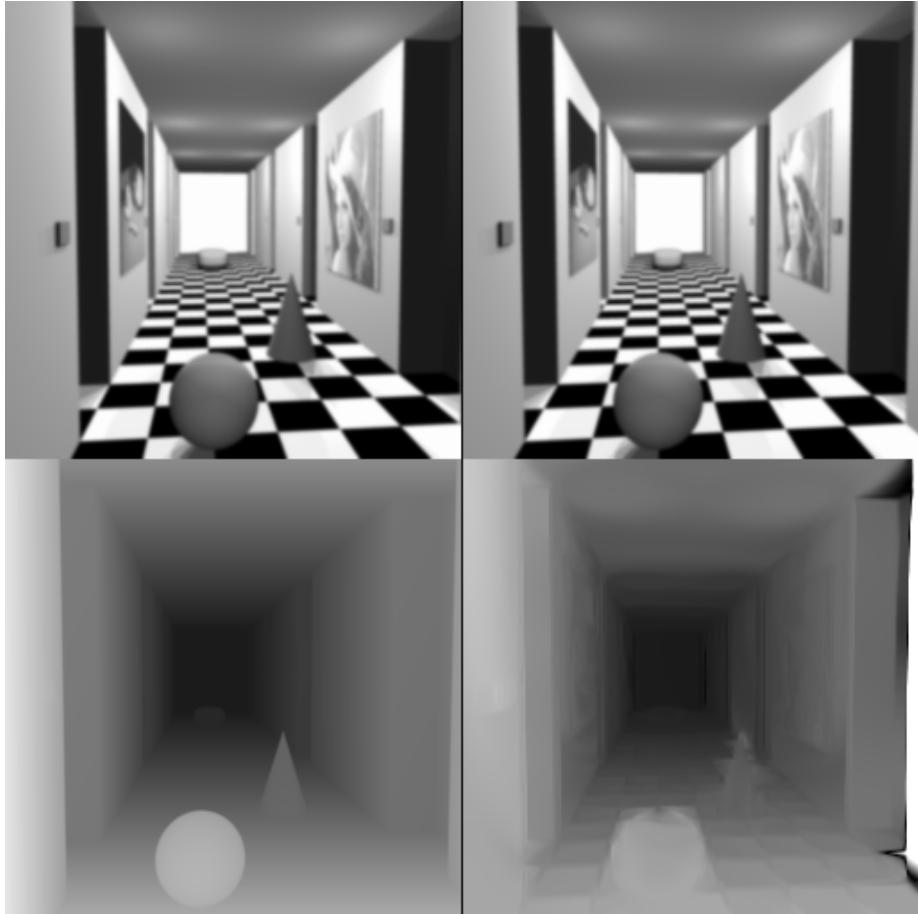


FIGURE 2.7: Depth Mapping Example. A stereo pair of images, with their exact disparity map bottom left and a disparity map produced by a dense disparity estimation algorithm bottom right- reproduced from [41].

2.6 Wireless Communication

The different methods of wireless communication available for a telerobotics system have varying requirements and benefits. For instance, the analogue video transmission found in FPV drone flying (as mentioned in Section 2.2.1) is low latency at the expense of video quality, range, and communication outside of line of sight. This is acceptable for flying a drone in an open field, but would not be adequate for controlling a telerobot from a VR headset in a completely different room as is the aim of this project. A better choice of communication method would be over Wi-Fi,

as it allows for communication across significantly longer distances and outside of line of sight. The trade off is an acceptable increase in latency.

The two most common Wi-Fi communication protocols are TCP (Transmission Control Protocol) and UDP (User Datagram Protocol). TCP is a connection-oriented protocol, so uses handshaking to guarantee reliable and ordered transfer of data [42]. The trade off to this is that the handshaking slows down the process of communication. UDP does not include this handshaking, so there is no guarantee that the packets will arrive, however they are sent with minimal overheads [43]. UDP is therefore the optimal choice for a system where throughput is of higher priority than packet reliability and ordering, such as the system presented by this report- images not arriving in the correct order and the occasional loss of packets would not have a significant effect on the functionality of the system in comparison to the usability improvement a reduction in latency provides.

Chapter 3

System Overview

The telerobotics system presented (Figure 3.1) consists of a fairly complex image processing pipeline running alongside a simple control system, with very little interaction between the two. The pipeline starts with the 2 cameras on the rover taking a picture each as close to simultaneously as possible. These images then get abstracted down to edge detected sets of lines, with a set of colours also generated from "Image 1" to combine with its edge detected version later on. These 3 pieces of data are then compressed into a single packet and transmitted via UDP to the server. The server splits them up again and produces a depth map from the 2 edge detected images. This depth map is passed to the 3D Environment to be used to produce a 3D model of the space the cameras were looking at. The server also combines the "Colour Data" and "Edge Detected Image 1" into a full coloured abstraction, which is overlaid onto the 3D model in the 3D environment. This environment is finally observed in the VR Headset.

The rover is controlled from an Xbox 360 controller that is connected to the server. Control inputs for driving the rover, gimble orientation, and parameters for the data abstraction (the only crossover between the control and image processing components) are transmitted to the rover at a fixed rate over UDP. It should be noted that in this system there is no connection between the orientation of the headset and gimble. The focus of this project was on providing the image processing foundations for future high presence systems, therefore the control system is the minimum required to explore the effectiveness of the chosen approach.

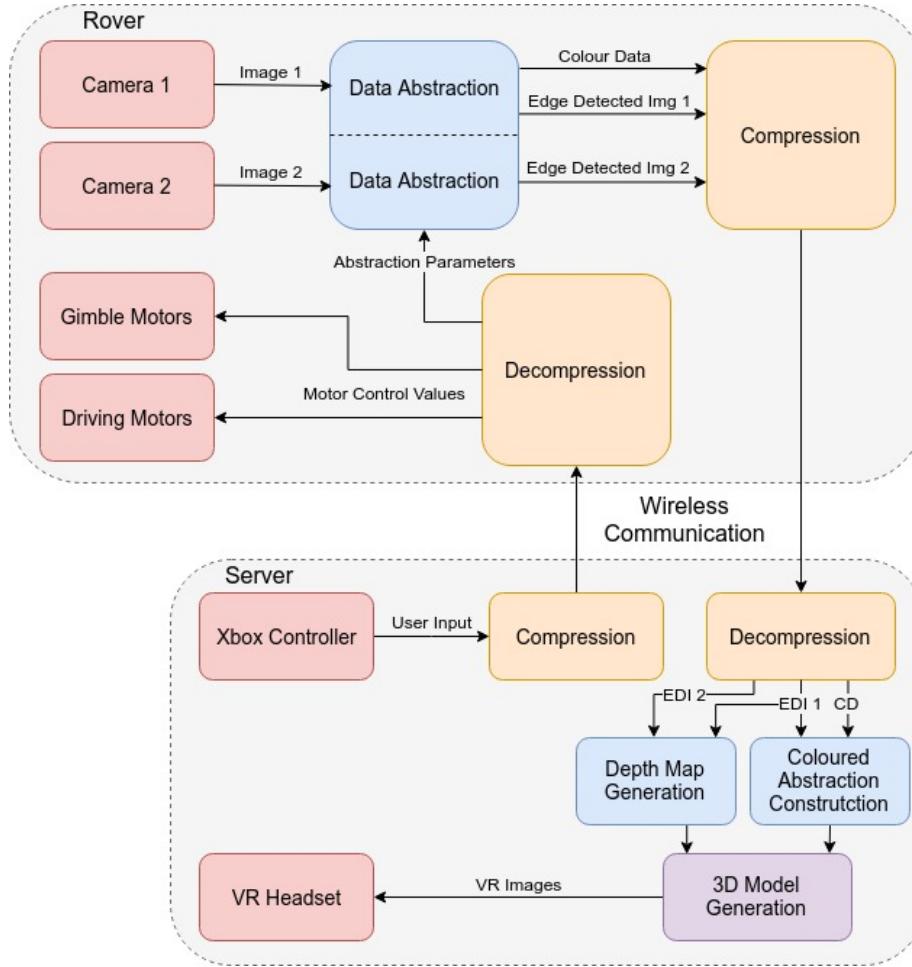


FIGURE 3.1: System Overview Block Diagram. The red blocks represent input/output, the blue blocks represent image processing steps, the yellow blocks represent communications, and the purple block represents the 3D environment.

Chapter 4

Abstraction Algorithm Development

In Section 2.3 we defined data abstraction as the reduction of an image down to only its most essential elements. What these essential elements are depends on the application, leading to a large range of possible methods and results. In this implementation of data abstraction the aim is to be able to navigate a telerobot from the resultant images, therefore the most important elements of each image are the size and shape of the objects in it. It is possible to convey the rough shape of an object by presenting its outline, therefore leading to edge detection being chosen as the first step of the algorithm. Identification of objects, while possible using edges alone, is significantly easier when colour is also provided. Most of the colours in an image, however, do not aid in object identification; one colour (preferably the average colour) for each object in the scene is sufficient. This leads to the algorithm presented in Figure 4.1, with examples of the abstractions it produces presented in Appendix A.

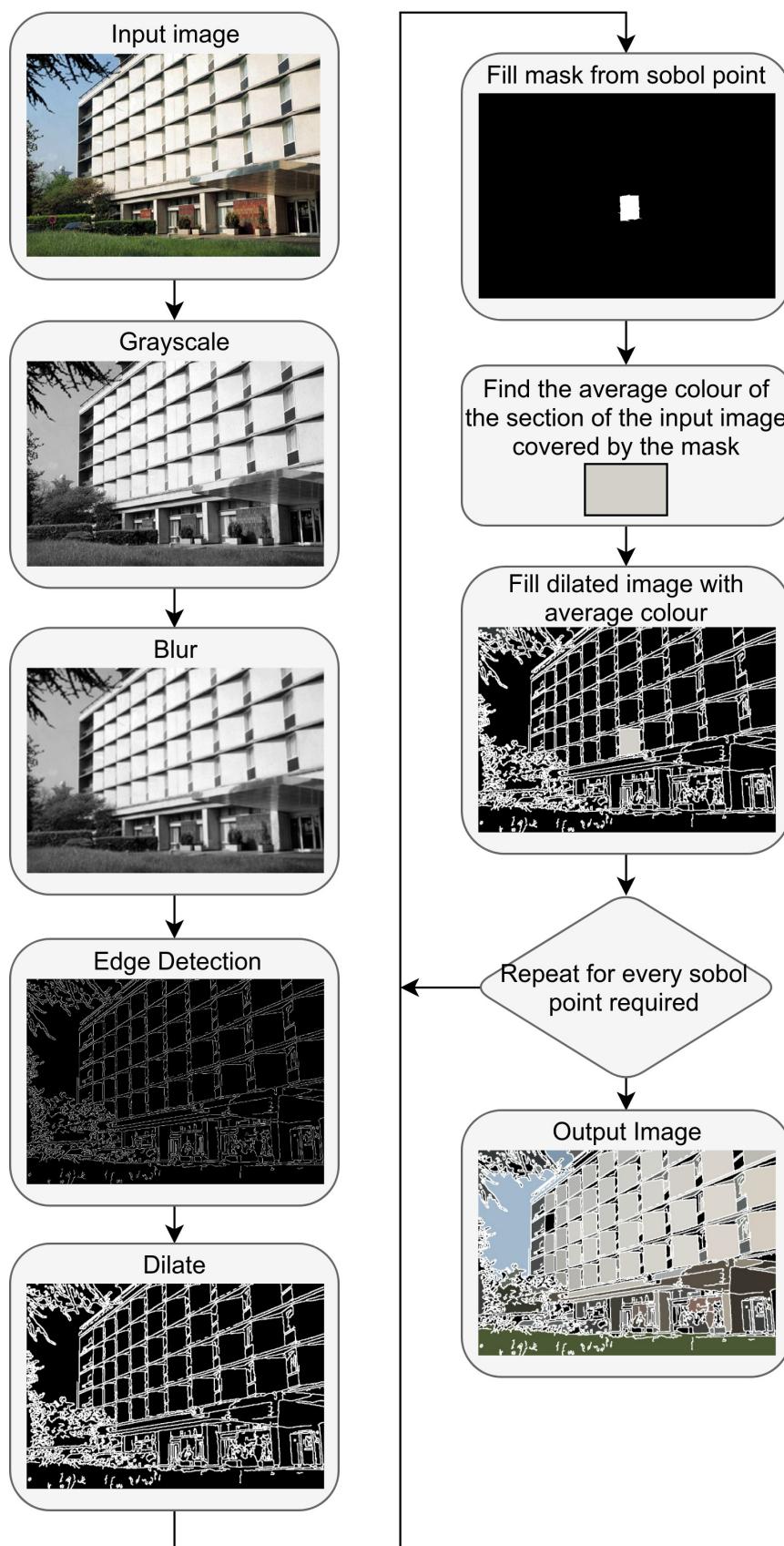


FIGURE 4.1: Data Abstraction Algorithm Process. The left half is explained in the "Edge Detection Process" section and the right half in the "Colour Averaging" section, both located below.

This chapter is presented in the context of the entire process occurring on a single computer; when incorporated into the final system, the whole process is undertaken on the rover apart from the "Fill dilated image with average colour" block, which is implemented on the server in its own loop through every sobol point ("Coloured Abstraction Construction" on Figure 3.1). It is also worth noting that this chapter is concerned with the algorithm's ability to produce recognisable abstractions under reasonable resource constraints, and not the file sizes of said abstractions. The file sizes it is capable of producing will be covered as part of the system testing and evaluation in Chapter 7.

4.1 Edge Detection Process

Canny edge detection was implemented using the Canny function provided by OpenCV [30]. The image is first converted into a grayscale format, as the edge detector detects large changes in intensity and not colour. The image is then blurred to remove any unnecessary edges and noise that may be picked up. The edge detection is applied, producing white lines representing the edges on a black background. The output of the edge detection is finally dilated to make the lines thicker and bridge the gaps between the lines that are very close together. This is done to reduce the number of lines produced by areas that are dense with detail such as hair and foliage and to bridge the gaps between lines that are close together, increasing the likelihood of defined shapes being created that can be easily flood filled later.

4.2 Colour Averaging

Flood filling was chosen as the method for applying colour to the edge detected image, as it is an effective method for filling spaces of unknown size and shape that are defined by high contrast boundaries. The OpenCV flood fill function requires a seed point to start flooding from, a colour to fill with, and parameters for the filling itself (unchanged from the defaults provided by the OpenCV documentation [44]).

4.2.1 Seed Points

Finding the points to flood fill from is a challenge, as each image will have a different number of spaces to be filled and the spaces can be of any size and shape. Three different methods were attempted to solve this problem. The first was an attempt to use OpenCV's contour functionality to turn the lines into a set of contours and use the centre of mass of each contour (an approximation of the centre of each space) as the seed point. Unfortunately, this was unusable due to high resource requirements. The method is detailed in Appendix [B](#).

Although it would be ideal to aim to flood fill from the centre of each space, it is only necessary if the intention is to be selective about which pixels are being used as seed points. It is possible to instead iterate through the whole image and flood fill from every pixel found that is not part of an edge or an already filled space. This method is effective at filling every space, and is also less resource intensive than the previous method. However, if presented with a complicated environment with many spaces to flood fill it must fill every single one, leading to unacceptable drops in frame rate.

A simple solution to the performance issues caused by complex images would be to set a maximum number of times flood fill can be used per image. However, if this is done then the seed points can no longer be selected by iterating through the whole image, as the presence of many small spaces at the top of an image would lead to larger, more important spaces not being filled at the bottom. The chosen solution to this issue is to select a set number of points quasi-randomly across the image using Sobol sequencing (explained in Section [2.4](#)). Although a certain number of points will land on lines and therefore not be used, if enough points are used then all the important spaces are filled without performance being heavily influenced by the complexity of the image as in the brute force method above (Figure [4.2](#)). However, complicated images will be processed with many of their denser areas unfilled (Figure [4.3](#)). It was decided that this was an adequate tradeoff for the performance improvements using sobol points provides, therefore the seed points are selected using this method in the final design.

Comparison of Brute Force and Sobol Point Performance

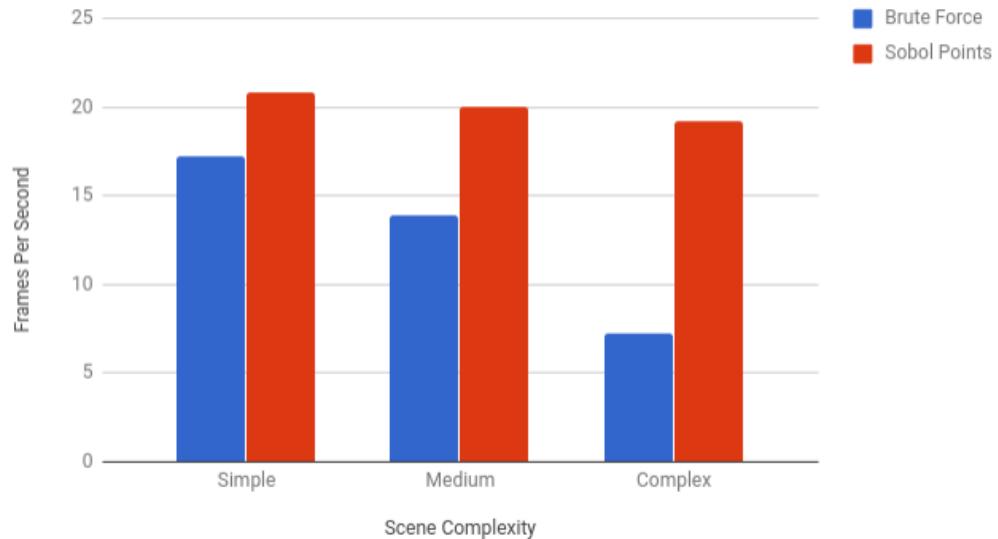


FIGURE 4.2: Performance Comparison of Seed Point Methods. It can be clearly seen that as the complexity of the scene increases, the brute force method results in unacceptable drops in frame rate, whereas the sobol method maintains a much higher degree of consistency. Images of the scenes used in this test can be found in Appendix C.

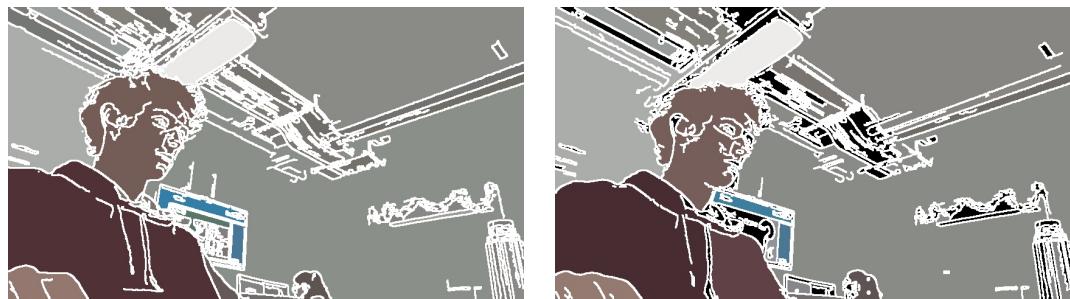


FIGURE 4.3: Comparison of brute force and Sobol seed point generation. It can be observed that the brute force method (left) accurately fills every space in the image, whereas using the Sobol method results in many unfilled spaces.

4.2.2 Fill Colour

Three different methods were considered for finding the colours that the edge detected image must be flood filled with. All three methods are valid solutions, but present

different ratios between accuracy and resource requirements.

Filling the abstracted image with the average colours of the objects present within the input image would be the clear optimal choice for the purposes of object recognition. However, the use of average colours is not essential; the objects in the scene are can still be recognisable with significantly lower colour accuracy. For this reason it would be acceptable to not find the average colour of the area being flood filled at all, and instead simply use the colour present in the input image at the seed point. This is a very fast method, however produces wildly inconsistent colours between images. This is because there can be a wide spectrum of colour across a single surface even within the threshold of Canny edge detection, and the Sobol sequence will not always sample from the same point in each new frame, producing spaces that flicker between a wide range of colours.

The consistency of the previous method can be improved substantially with minimal impact on performance by taking an average of the colour within the area of a small circle around the seed point, rather than just the colour of that one point. This significantly improves the consistency between images, however introduces the problem of incorporating pixels from outside the space in question. This is due to the quasi-random points often being so close to the edge of the space that the averaging circle crosses the edge slightly and incorporates part of a neighbouring space in the average. Therefore, the size of the circle must be carefully selected to balance the benefits of increasing size (more consistency when the seed point is near the centre of the space) and the benefits of decreasing size (more consistency when the seed point is closer to the edge).

The OpenCV flood fill function provides the ability to fill a blank mask using the boundaries defined by a different image [45]. This makes it possible to create a custom mask with the exact size and shape of the space that is to be filled and use that to find the average colour instead of a predefined circle. This produces the average colour of every space in the image exactly at the expense of adding an extra stage of flood filling before the edge detected image itself is filled (a stage of flood filling that has to be undertaken on the rover in the full system). The consistency between images for this is the maximum possible based on colour alone (Figure 4.4), though inconsistency in the edge detection causes certain spaces to combine and divide constantly, leading to a small amount of colour inconsistency to remain

regardless. The fact that this method leads to flood filling being undertaken on the rover as well as the server leads to performance concerns, however the consistency it produces led it to be the chosen method to be implemented into the full system.

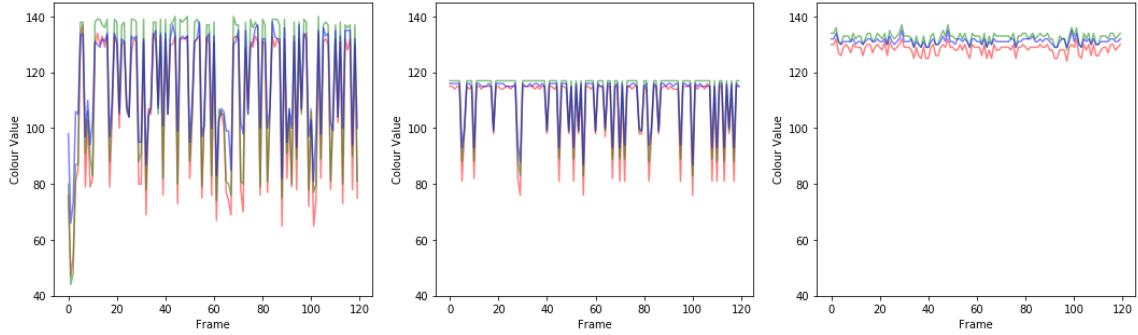


FIGURE 4.4: Comparison of Colour Averaging Methods. These are RGB values over time produced by flood filling an example area using the colour of the seed point (left), circle average (middle), and flood fill average (right). The increase in consistency from left to right is very apparent.

Chapter 5

Rover Implementation

Due to the rover simply being a test platform, its hardware is fairly simple. It consists of a chassis containing batteries, a power distribution board, motor drivers and motors used to drive the rover's wheels, with the central computer (Raspberry Pi 3 [46]), gimbal, and gimbal control circuitry all mounted on top (Figure 5.1, 5.2). A detailed breakdown can be found in Appendix D. The application of computer vision techniques in an embedded system has high processing requirements, leading to the selection of a Raspberry Pi 3 as the core of the system (it was the highest performance embedded device readily available).

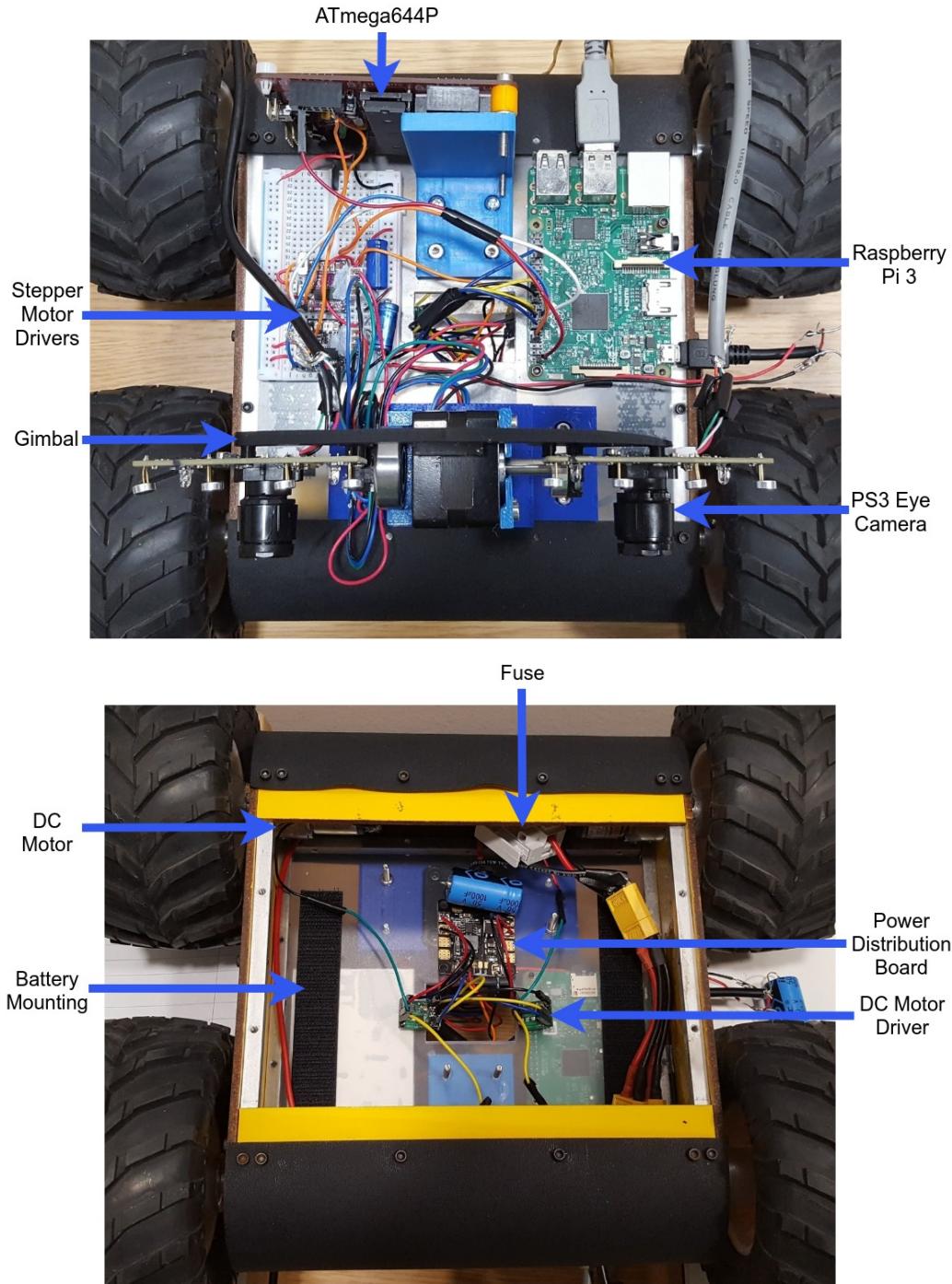


FIGURE 5.1: Rover Internals. The top picture is a top-down view of rover, in which you can see the Pi, gimbal control circuitry, and gimbal. The bottom picture is of the inside of the rover, taken through a hatch in its underside. In this picture you can see velcro strips marking where the batteries are mounted, power distribution board, safety fuse, 2 DC motor drivers, and 2 of the 4 DC motors.

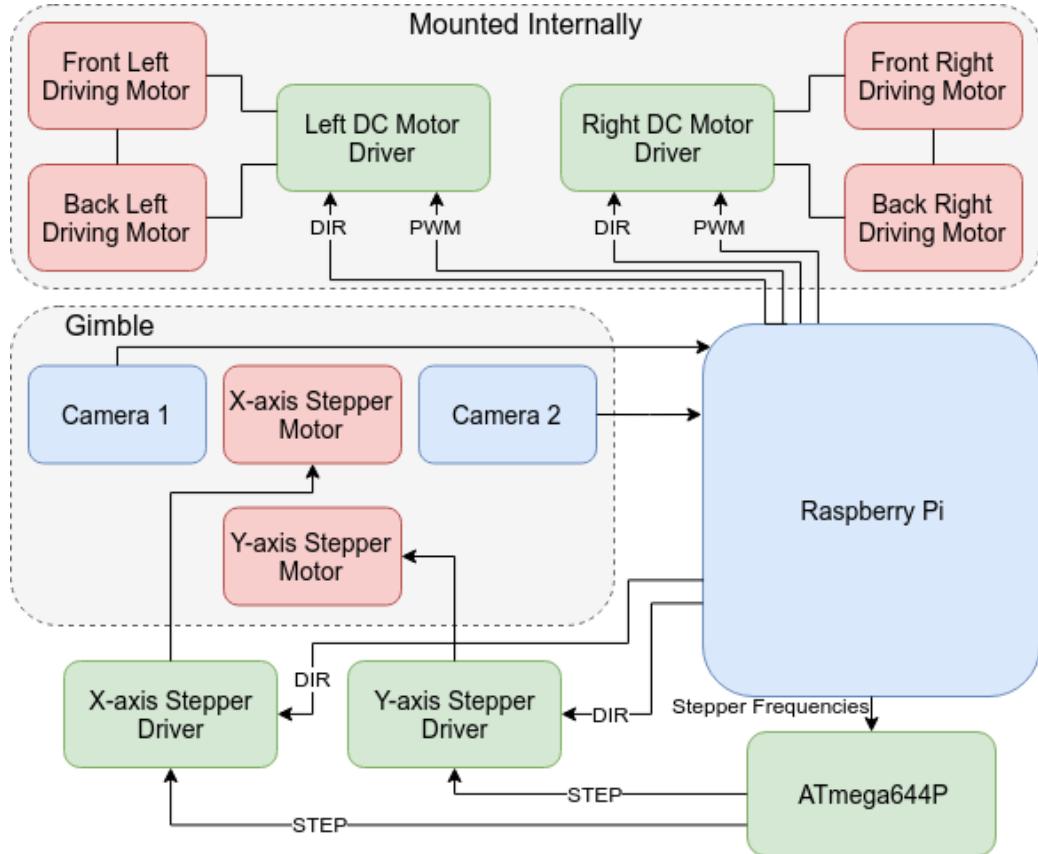


FIGURE 5.2: Hardware Block Diagram. The red blocks are motors, green blocks control system components, and blue blocks parts of the image pipeline.

5.1 Gimbal Design

The choice of cameras had to fulfil a very specific set of requirements. The two cameras must be same, as any differences in the images due to using different lenses or sensors would reduce the quality of depth map produced on the server. This makes the most obvious camera choice, the R-Pi camera module, unusable, as the Pi cannot interface with two simultaneously. The two cameras must also be able to take pictures on command from the Pi with low latency, reducing the possible options down to primarily USB webcams. Finally, they must have a high shutter speed. Any motion blur in the images will blur all the edges they contain, making them undetectable by the edge detection algorithm, and any morphing of the image while under motion due to the time it takes the shutter to pass across the entire

sensor will once again reduce the quality of the depth map. A high shutter speed reduces motion blur and shutter related morphing, therefore making it essential for whenever the rover is in motion. This requirement reduces the possible cameras down to primarily dedicated computer vision cameras, however these are expensive and often too large to build a gimbal for without also buying expensive motors.

Only one camera was found that fulfilled all these requirements whilst also being reasonably priced- the PlayStation 3 (PS3) Eye. The PS3 Eye is a peripheral for the PS3 that facilitates games that incorporate aspects of computer vision, so it is designed with computer vision and value for money in mind. While the image quality is fairly poor, this does not significantly impact the quality of the abstractions the system produces due to most detail being discarded as part of the process. The only real flaw in using the PS3 Eye in this system is its poor dynamic range; if the camera is aimed at a window during the day, all the colours in the room will become unrecognisably dark. However, the PS3 Eye has such impressive shutter speed and latency for the price point that this deficiency is an acceptable trade off.

The design of the gimbal (Figure 5.3) has considerable impact on the 3D model the system generates. As mentioned in Section 2.5.3, the images must be rectified to account for discrepancies in the mounting before the depth map is generated on the server, therefore the closer the cameras are to parallel with each other, the less severe the rectification applied must be. Similarly the stability of the gimbal is very important, as any vibrations will cause inconsistency in the alignment of the cameras, leading to inaccurate depth maps. This led to the chosen design where the X-axis (tilt) motor is located centrally, between the cameras, to balance the weight around the rotational axis of the y-axis (rotation) motor. The 3D-printed part the cameras are attached to is also stabilised through mountings on both sides of the x-axis motor, using a ball bearing on the side not driven by the motor.

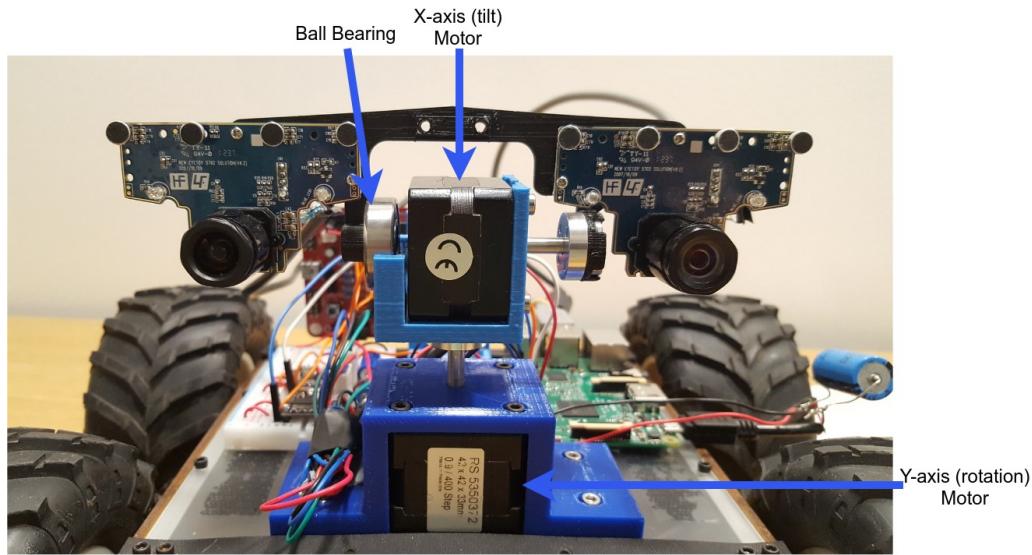


FIGURE 5.3: Gimbal Picture. The Y-axis motor is housed at the bottom, with the X-axis motor directly above it. The ball bearing that stabilises the non-driven side of the cameras' backplate can be seen to the left of the X-axis motor.

Another important aspect of the gimbal design is the distance between the camera lenses. The further apart the two cameras are, the closer distance objects will be in the depth map. Ideally we would aim to match the interpupillary distance of human eyes (63mm on average [47]), so objects in the 3D environment appear as close as they would were the user standing in the place of the robot. However, with the X-axis motor located centrally it is not possible to mount the cameras that close together. The inter-lens distance in the final design is 120mm, as this is the closest distance possible without reducing the stability of the gimbal. While not ideal, it simply results in objects appearing closer in the depth map than they actually are, and the distance from the cameras where an object is too close for the depth mapping algorithm to match it between the two images (the cameras are "cross-eyed" if you will) being extended.

5.2 Image Pipeline

As established in Chapter 3, the rover takes a picture with both cameras, abstracts those images, then sends that data off as a single combined packet to the server.

While Chapter 4 discussed the abstraction process as a single step that produces a full abstraction with both edges and spaces filled with colour, this does not reflect the implementation utilized in the full system. The final step of filling the spaces in the edge detected image using the selected seed points and average colours is completed on the server, not on the rover. Also, only one of the two images needs colour information at all, as the edges are the only part of the abstraction required to produce the server depth maps; the colours are to be used as part of a texture applied to the 3D model produced from the depth maps, therefore only one set is required. This results in the data packets being sent to the server consisting of two edge detected images and a set of seed points with corresponding colours for one of the images.

Attempts to implement this process on a single thread on the Pi, as tested successfully on a laptop, either crashed the Pi or would produce an unacceptable frame rate of around 1fps. To rectify this, both pipelining and parallelism were utilized to make better use of the Pi's quad core processor (Figure 5.4), and compromises were made in the quality of the abstractions to reduce the workload.

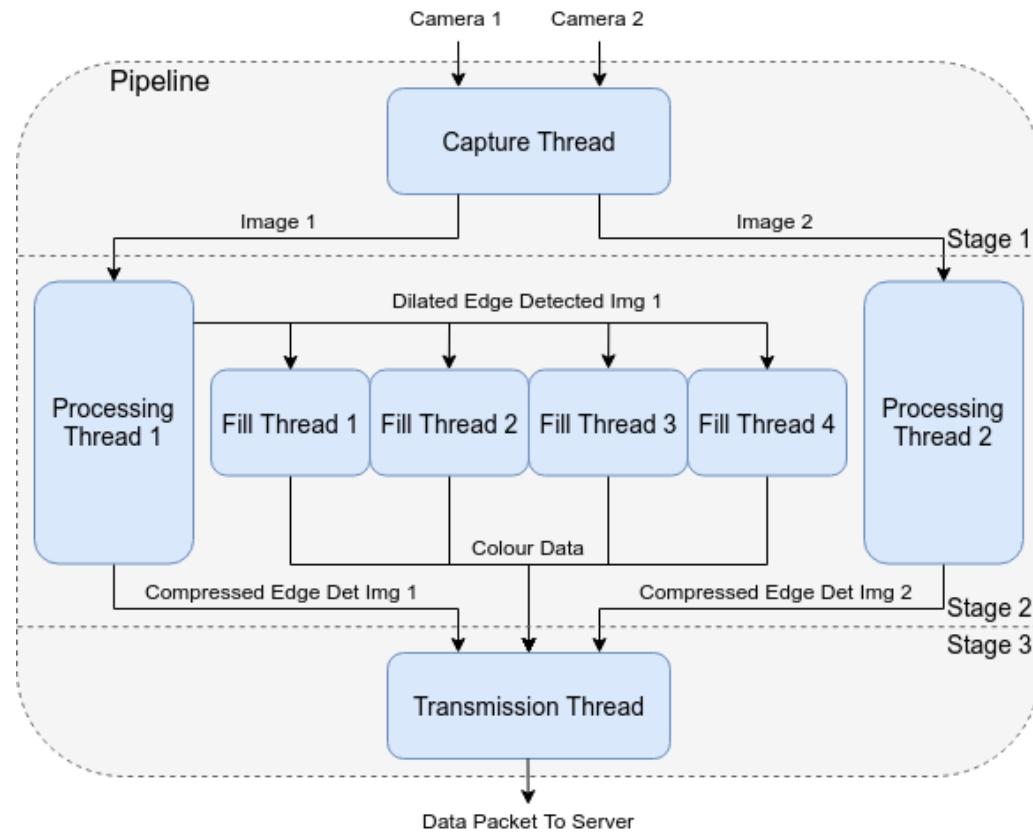


FIGURE 5.4: Raspberry Pi Image Pipeline Threading Block Diagram.

The capture thread handles signalling the cameras to capture and decoding the images. The capturing and decoding are done as separate operations in an effort to take the images as close to simultaneously as possible in a single thread. The first compromise in quality in favour of performance is made here, where the images are captured with a resolution of 320x240 rather than the cameras' standard resolution of 640x480. As will be discussed in greater depth below, the highest workload task in the pipeline is flood filling. Reducing the pixel count of every space by a factor of four therefore provides a significant improvement in performance. The smaller images also have the benefit of lower detail in high detail areas, so sections that would become areas of dense lines when edge detected (examples of this effect can be found in Appendix A) are significantly less dense, containing less extraneous data.

The processing threads are concerned with the edge detection and compression of the images. The edge detection process is mostly as described in Chapter 4; the only difference is that only the image being sent from "Processing Thread 1" to the fill

threads undergoes the final dilation step. The purpose of the dilation is to bridge gaps between the edges, creating defined shapes for the flood fill process. A side effect of dilation is a reduction in edge accuracy, which is very important when the images are to be used to produce depth maps later on. This leads to the logical conclusion that the images should be sent without dilation, and dilation only applied to find the colour data in the fill threads and then again on the server to create the complete coloured abstraction, allowing the depth maps to be constructed from non-dilated edges.

While it can be induced from comparing the original images to their edge detected versions by eye that the latter contains less information than the former, this will only be reflected in real numbers if file format and compression are considered carefully. When the common image formats are compared, PNG would appear to be effective for this use case [48], as it excels at efficiently storing large blocks of the same colour (most of each edge detected image is black space). When tested on the edge detected images (Figure 5.5), it was confirmed that PNG provides the lowest file sizes, and compression level 5 provided the best ratio between file size and compression time (using the imencode function in OpenCV). More intelligent compression was tested using libimagequant [49], however it resulted in very poor performance (<2fps) with negligible improvement to the level of compression. An alternate option to compression as a bitmap was vectorising the images, however this was inaccurate and not as effective as bitmap compression (more information can be found in Appendix E).

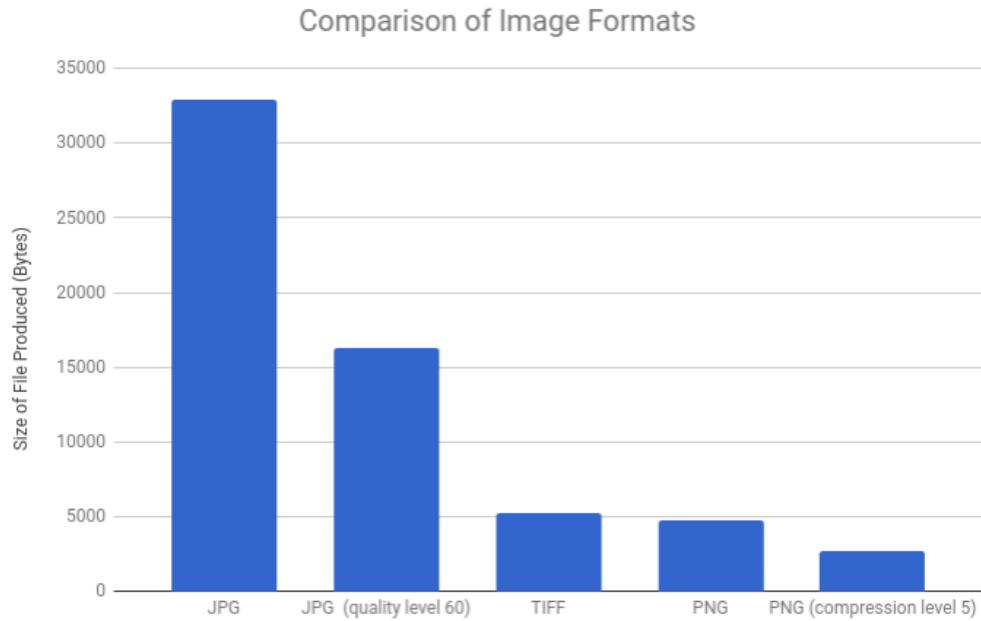


FIGURE 5.5: Comparison of Image File Formats. This data shows that PNG provides the smallest file sizes of the readily available file formats. It also shows that both standard JPG and PNG compression are very effective at reducing file size, however attempting to compress the JPG versions enough to compete with PNG would result in images of unusably poor quality (quality level 5-10).

The stage in the image pipeline that has the highest performance impact is the colour averaging, due to its use of flood filling. As the number of spaces being flood filled is determined by the number of points from the sobol sequence that hit unfilled spaces, the number of sobol points used is an important variable in tuning the performance of the system. In the testing done on a laptop in Chapter 4, the number of sobol points being used per image was between 400 and 600, and this filled a reasonable number of spaces while providing a reasonable frame rate. When this was attempted on the Pi however, the frame rate was below 1fps. This called for a significant reduction in sobol points and the application of parallelism. Good performance was achieved using 4 threads dedicated to the flood fill colour averaging task, each taking 50 sobol points. A total of 200 sobol points is a significant reduction from the laptop implementation of the algorithm, however it must also be noted that the images being used are much lower detail, so do not require a large number of sobol points to be mostly covered (Figure 5.6).

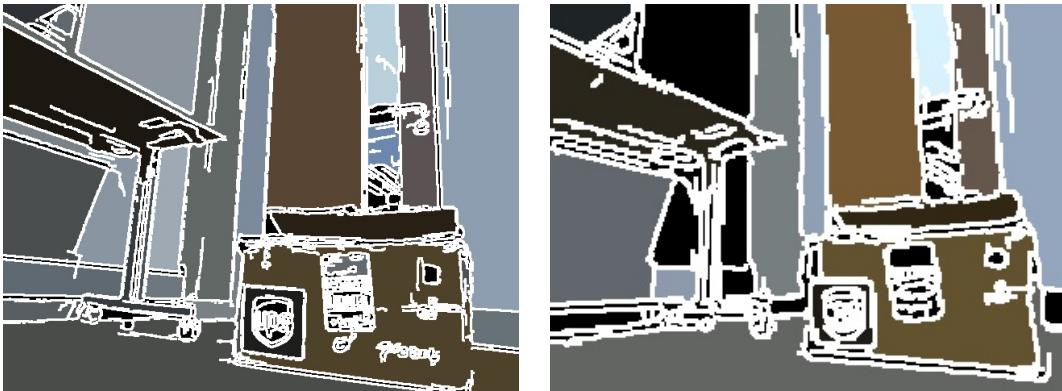


FIGURE 5.6: Comparison of Laptop and Rover Abstraction. The laptop abstraction (left) is high resolution, with only the smallest of spaces remaining unfilled such as the detail on the box stickers. The rover abstraction (right, this image being after the colour data and edge detected image had been combined on the server) is much lower resolution, with many more spaces remaining unfilled. However, it is still clearly the same scene with the geometry represented with almost the same level of accuracy, therefore making it an acceptable abstraction.

While it may seem as though the parallelization of this process could cause issues if two threads are attempting to fill the same space in the image simultaneously, this simply results in two successful seed points with slightly inaccurate average colours assigned to them, and only one of them being used to create the complete abstraction on the server. As the colours of the spaces are only recorded to provide the user a better understanding of the objects in the environment, it is not concerning if occasionally one is not an exact average.

Once the three pieces of data for an image pair (two compressed edge detected images and a set of colour data) have been generated, they must be combined into a single packet and sent to the server; this is covered by the transmission thread. While the images are at this stage already compressed into a set of bytes that can be transmitted as is, the colour data needs its own custom packaging. Each seed point-average colour pair is formed into its own sub-packet with the structure shown in Table 5.1. These sub-packets make up the colour data data segment within the complete data packet.

TABLE 5.1: Colour Data Sub-Packet Structure. The seed point components are given 2 bytes each due to their maximum values being larger than a single byte can store.

Byte in Colour Data Sub-Packet	1	2	3	4	5	6	7
Usage	Seed Point			Average Colour			
Component	X	Y	Red	Green	Blue		

As the size of each data segment is unknown and highly variable, knowing where one ends and another begins on the server is a challenge. The solution utilized in this instance is separating each data set with a splitter made up of 7 bytes that contain 0, 1, 2, 3, 4, 5, and 6. This sequence of bytes is extremely unlikely to occur within the data, so can be easily used to pinpoint the starts and ends of the data sets. This therefore leads to the data packet format shown in Table 5.2.

TABLE 5.2: Data Packet Format.

Data Segment	Colour Data			Splitter	Img 1	Splitter	Img 2
Contents	Sub-Packet 1	Sub-Packet 2	...	0...6	PNG Data	0...6	PNG Data

5.3 Control System

The primary aim when designing the control system was to make controlling the rover easy and intuitive; the user must have no trouble understanding the controls whether in or out of VR. The obvious first consideration for the control input method is through a keyboard and mouse, as this is standard practice in teleoperations. However, operating a keyboard whilst in VR is very difficult, as the user must be able to see both their hands and the keyboard to know which keys they are pressing. A better direction would be to consider the standard input methods used in VR gaming, as these are known to be intuitive without requiring that the user's hands be visible. The most common VR input methods are dedicated VR controllers, such as the Vive controllers, and standard gamepads, such as the Xbox 360 controller (Figure [CONTROLLERS?]). Due to being visible within the VR environment (they are tracked like the headset), the Vive controllers are the most intuitive method within VR, however they cannot be used outside VR, so do not facilitate testing the control

system without an active VR headset connected. The Xbox controller is a great general use controller, as it can be integrated into almost any system and can be used both with and without a VR headset, leading it to be selected as the control input method.

The motion of the rover is restricted to forwards or backwards with variable speed, or rotation with a fixed speed. This is so the rover is forced to only rotate in short intervals, as rotation causes a reduction in depth map accuracy that forward and backwards motion does not (the extent and causes of this will be discussed in Chapter 7). The user has the ability to chose between full and half speed drive modes, to provide the flexibility of both being able to run the motors at full power in one mode and drive at low speeds with greater control in the other. Due to the gimbal not having a full range of motion (it can rotate roughly 200 degrees before it starts to pull its own cabling out), its range must be restricted in software. This is done by keeping track of the number of steps the stepper motors have undertaken as an estimator of the gimbal's orientation and preventing it from moving past certain angles. This system is effective, however the limits drift over time due to the stepper motors not always moving through the exact same number of steps requested by the control system. This drift, while not ideal, is only an issue over long activation periods, so is not a major concern for this project. The final element the user has control over is the low threshold in the edge detection applied as part of the data abstraction (this is the single point of contact between the image pipeline and control system that is mentioned in Chapter 3). Changing the low threshold of the edge detection changes the amount of detail in the 3D model, having a major impact on its quality. Additionally, the threshold level that produces the optimal level of 3D model detail changes depending on the space the rover is observing, therefore it is essential that the user has control of this at run-time.

The user inputs are transmitted to the rover over UDP, each packet with the structure shown in Table 5.3. The packets are sent at a constant rate of 50 per second, even when the user is not inputting any commands. This is so that in the event that the wireless link is failing, the inconsistency of the constant message stream will notify the rover that there is an issue. When the rover detects that it has been an unreasonable amount of time since the last message, it stops all its motors until it

starts receiving messages again, to prevent it from damaging itself while the user has lost control.

TABLE 5.3: Control Data Packet Structure. The analogue stick axes are mapped to between 0 and 255 to fit them within a byte each, as greater accuracy than that was not required. The low threshold only being allocated a byte means it is also capped at 255, however through testing it has been determined that values even above 100 produce images with no edges anyway, so this limit is not a concern.

Byte in Control Packet	0	1	2	3	4	5
Usage	Driving Control (Left Analogue Stick)		Low Threshold	Gimbal Control (Right Analogue Stick)		Drive Mode
Contents	X-axis	Y-axis	Threshold Value	X-axis	Y-axis	0/1

Chapter 6

Server-Side Implementation

The purpose of the server is to receive image data from the rover, produce a 3D environment from this data, and feed back control inputs from the user. This is all done within the framework of the 3D game engine Unreal Engine 4 [50]. Unreal 4 was chosen because it supports almost any VR headset on the market, is simple to integrate with OpenCV, and is free to use. The structure of any Unreal program is very complicated, as the engine does a lot in the background across many threads. The implementation of this project within the Unreal environment (Figure 6.1) consists of a receive thread that receives images, processes them, then updates the 3D model, and a portion of the game thread (the Unreal thread that handles game logic) that handles and sends user input 20 times a second. The fact that the 3D model is updated on a thread separate to the rendering of the images that are sent to the headset is what allows the headset to run at an unrelated and significantly faster frame rate than the model is being updated at.

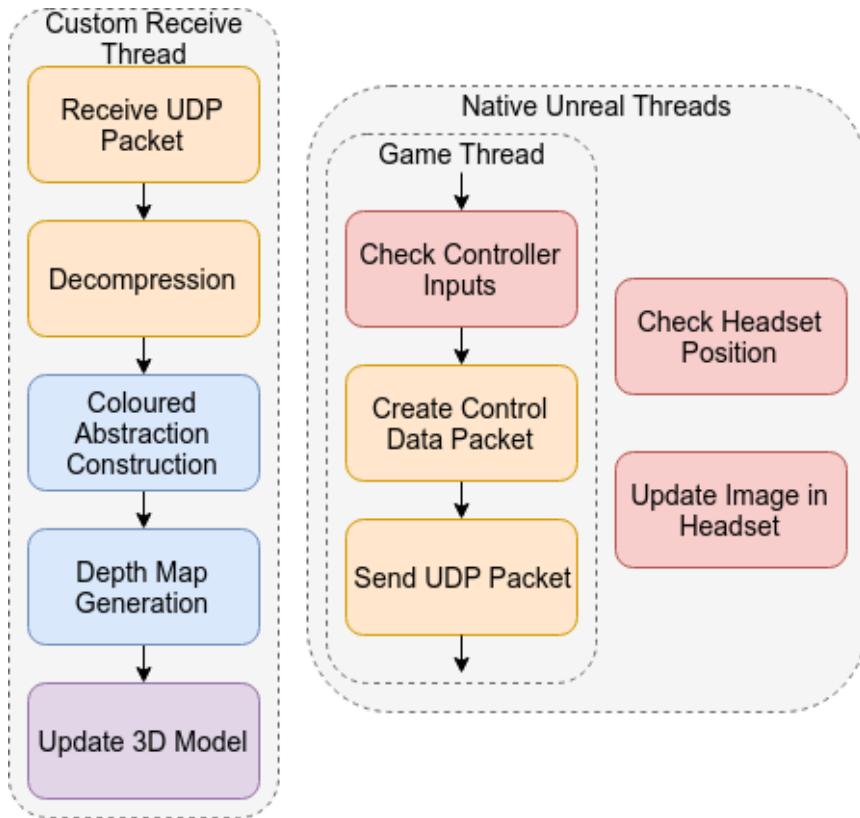


FIGURE 6.1: Server Program Structure. Red blocks are standard Unreal functionality, yellow blocks are communications related, blue blocks are OpenCV based, and the purple block is custom integration with the Unreal environment. The blocks within the game thread run 20 times a second. When these blocks are not running, the game thread is handling other game logic within the environment.

6.1 Depth Map and Abstraction Construction

For a depth mapping algorithm to function accurately, the 2 images it receives must be rectified (established in Section 2.5.3). The rectification parameters for the cameras in our system have been calculated using a set of programs provided by Sourish Ghost [51]. The rectification is applied using these parameters just before the depth maps are calculated (Figure 6.2).



FIGURE 6.2: Demonstration of Stereo Image Rectification. The original left and right images are shown top left and top right, with their rectified counterparts bottom left and bottom right. It can be seen that the features of the bottom images are better matched vertically than in the original images.

When selecting a depth mapping algorithm, the major factors to consider were speed and performance with abstracted images. The use of abstractions makes demonstrations of the algorithms with normal images of little help; there is no guarantee that the algorithms would be able to map depth for edge detected lines with the same accuracy, if at all, since this is not what they were designed for. Three different depth mapping algorithms were tested: StereoBM, StereoSGBM, and Libelas. StereoBM and StereoSGBM are a block matching and semi block matching algorithm provided by OpenCV [30], and Libelas is a more complex algorithm provided by the Autonomous Vision Group [52]. Of the three algorithms presented, StereoBM is the fastest and Libelas the slowest (Figure 6.3).

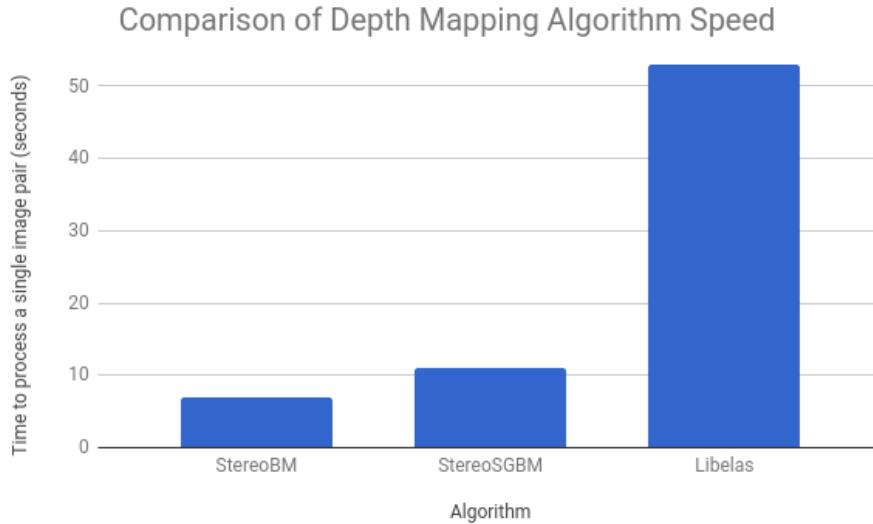


FIGURE 6.3: Comparison of Depth Mapping Algorithm Speed. The test images used to produce this data were the rectified images presented in Figure 6.2. These same images were used in the production of all further figures in this section.

When tested on images received from the rover, StereoBM and StereoSGBM produced noisy results, yet, if inspected closely, results that include reasonable depth information along the areas where edges were in the original images (Figure 6.4). Libelas, however, did not produce results that were in any way recognisable. Combining this with its significantly slower processing speed, it is clear that Libelas is not that correct choice for this use case.

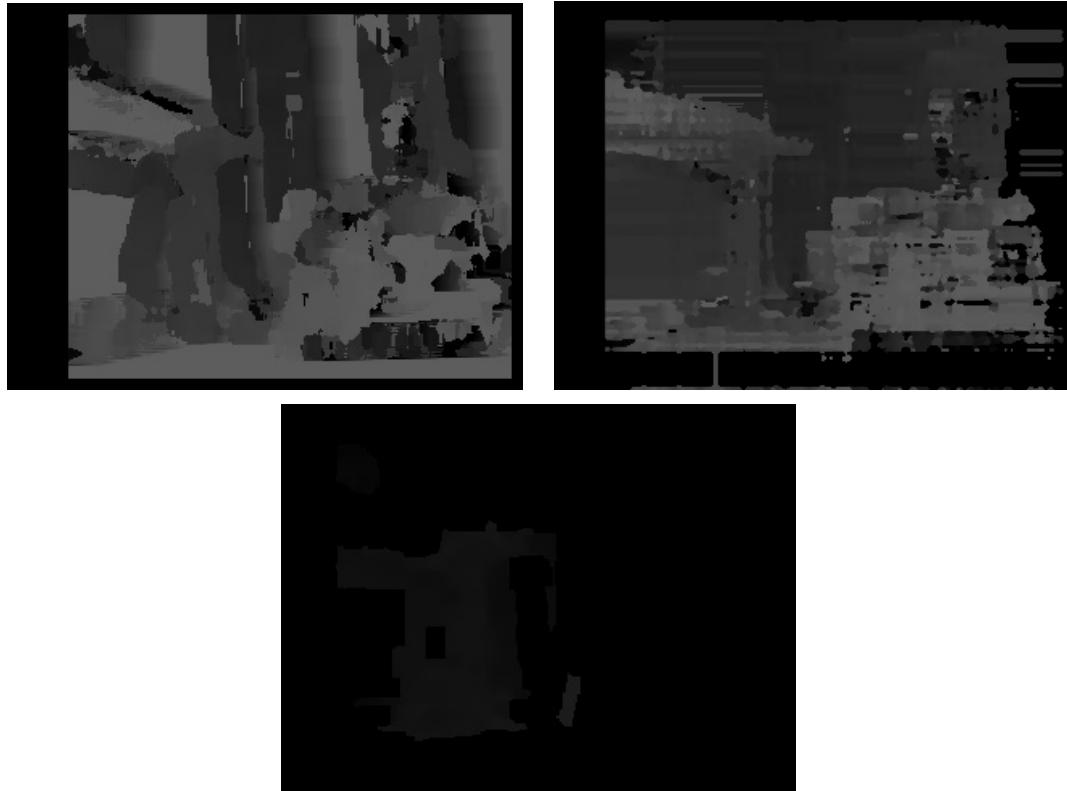


FIGURE 6.4: Comparison of Raw Depth Mapping Algorithm Output. The StereoBM output (top left) is very noisy, however correct depth can be seen on the box in the bottom right and on the table in the top left (when compared to the input images in Figure 6.2). The StereoSGBM output (top right) shows similar results, though with a significant reduction in noise. The Libelas output (bottom) shows very little- it does not seem to work with edge detected images whatsoever.

To be able to compare StereoBM and StereoSGBM further, the noise their outputs contain must be filtered out. This can be achieved by applying Weighted Least Squares filtering to the depth map (Figure 6.5). This is effective in producing consistent depth across the objects in the map. Unfortunately, regardless of the angle to the camera that an object sits at, the filtering will often assign it a single depth across the whole surface. This results in surfaces like the floor or the ceiling being inaccurately represented as a vertical plane very close to the camera, however most other objects are not significantly affected.

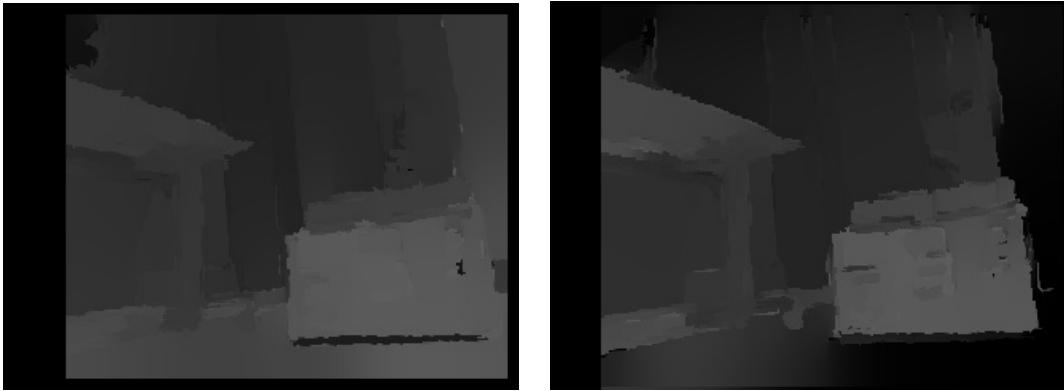


FIGURE 6.5: Filtered StereoBM and StereoSGBM Outputs. The StereoBM output (left) has been improved significantly by the filtering, with mostly consistent and correct depth across all objects other than the floor. StereoSGBM (right) has been similarly cleaned up, however has not provided depth for the floor or right wall whatsoever. The single section of floor it attempted (under the table in the bottom left) is the same incorrect depth as produced by StereoBM.

When comparing the filtered maps, there are very few differences. Both are reasonable representations of the original scene, and when one makes a mistake in the depth of an object, the other will probably make the exact same mistake. The only major difference is that StereoBM will consider the floor incorrectly as a vertical plane close to the camera, whereas StereoSGBM will incorrectly not record a depth for it at all. This lack of a significant gain in quality when using the noticeably slower StereoSGBM led to StereoBM being chosen as the algorithm used in the final system.

While the individual depth maps (post filtering) are reasonable approximations of the space being viewed, the depth of a single object will be inconsistent between frames, due to inconsistencies between the edge detected frames they were produced from. When viewed as a video feed, most objects will oscillate slightly, with greater oscillations in objects that are more ambiguous or less consistent in the edge detected frames. This issue is mitigated in the system by taking a running average, the weighting of the frames in the average reducing with the age of the frame. This increases consistency substantially at the expense of a minor reduction in responsiveness.

The construction of the coloured abstraction is as addressed in Chapter 4. The seed point/average colour pairs are each used to flood fill "Edge Detected Img 1" from

Figure 3.1, producing the full abstraction that is to be applied as a texture to the 3D model generated from the depth maps.

6.2 3D Model Generation

To generate a 3D model dynamically based on image data, an Unreal Engine 4 class that allows for mesh generation at run-time is required. Although more intelligent options are available as add-ons, the core Unreal 4 class "procedural mesh" was selected due to its simplicity and compatibility with OpenCV. The class is used as a basis for the generation of a grid based mesh (Figure 6.6).

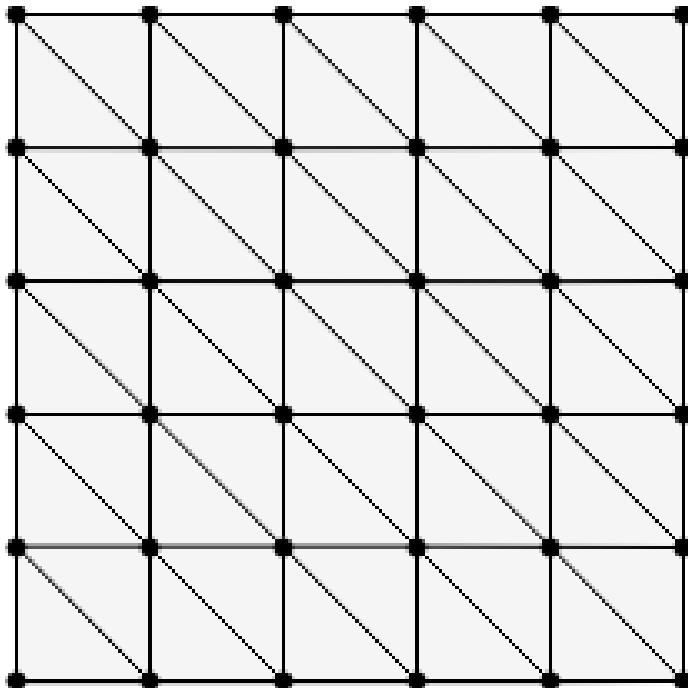


FIGURE 6.6: Mesh Grid Segment. Each corner of the grid is a vertex, with triangles formed from the vertices. The grid is built in the X-Y plane, leaving the Z component of each vertex available to be easily assigned depth.

Each pixel in the depth map is mapped to a vertex in the mesh, resulting in a grid of 320x240 vertices for 320x240 pixel images. The colour value of each depth map pixel is mapped to the Z component of its corresponding vertex, leading to the bright pixels in the depth map (close objects) generating vertices that are pushed forward

from the grid. When this grid is placed an appropriately realistic distance from the user in the headset, the close objects in the depth map will be pushed closer to the user and the further objects will remain closer to the grid, further from the user. When the full coloured abstraction is then applied to the mesh as a texture, the pixels once again mapping 1:1 to the vertices, the space the rover is observing is finally being portrayed in VR (Figure 6.7).

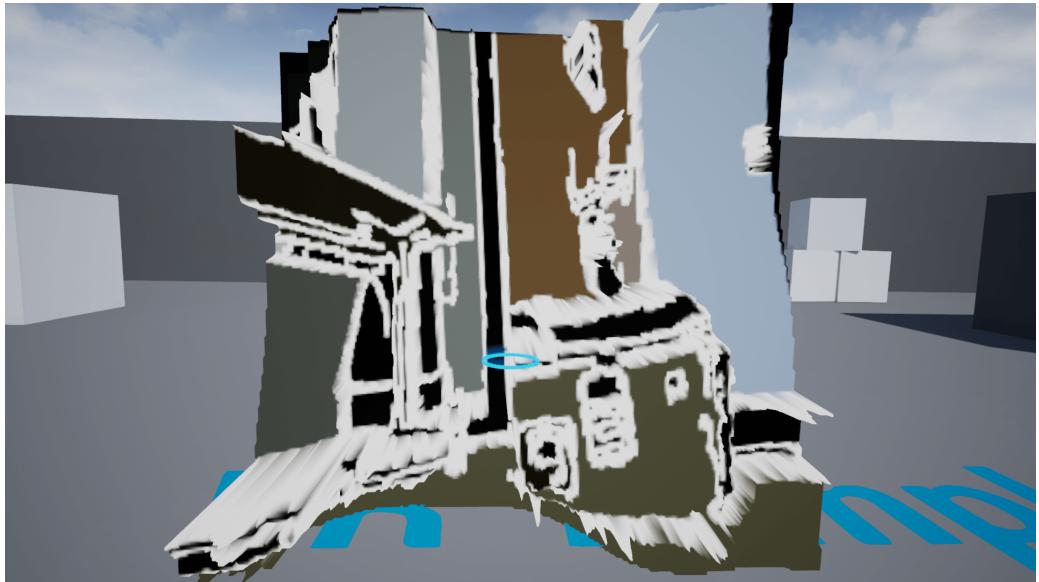


FIGURE 6.7: Final Textured 3D Model.

Chapter 7

Testing and Evaluation

Chapter 8

Project Management

Comparison of product and brief Evaluation of project management

Chapter 9

Conclusion

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Appendix A

Demonstrations of Full Data Abstraction



FIGURE A.1: Demonstration of full abstraction process. The final parameters and methods (of those under discussion) are a blur kernel of 5x5, a low threshold of 25 (for this example), Sobol seed point generation, and averaging via preliminary flood fill. It can be seen that most areas of the image are being effectively edge detected and flood filled with the correct colours; however, some areas are hard to interpret such as around the bushes in the bottom left, and some spaces have been left unfilled such as the panel below the top left corner of the building. These issues are minimal though, therefore leading me to conclude that the process is effective at producing recognisable abstractions of the input images.

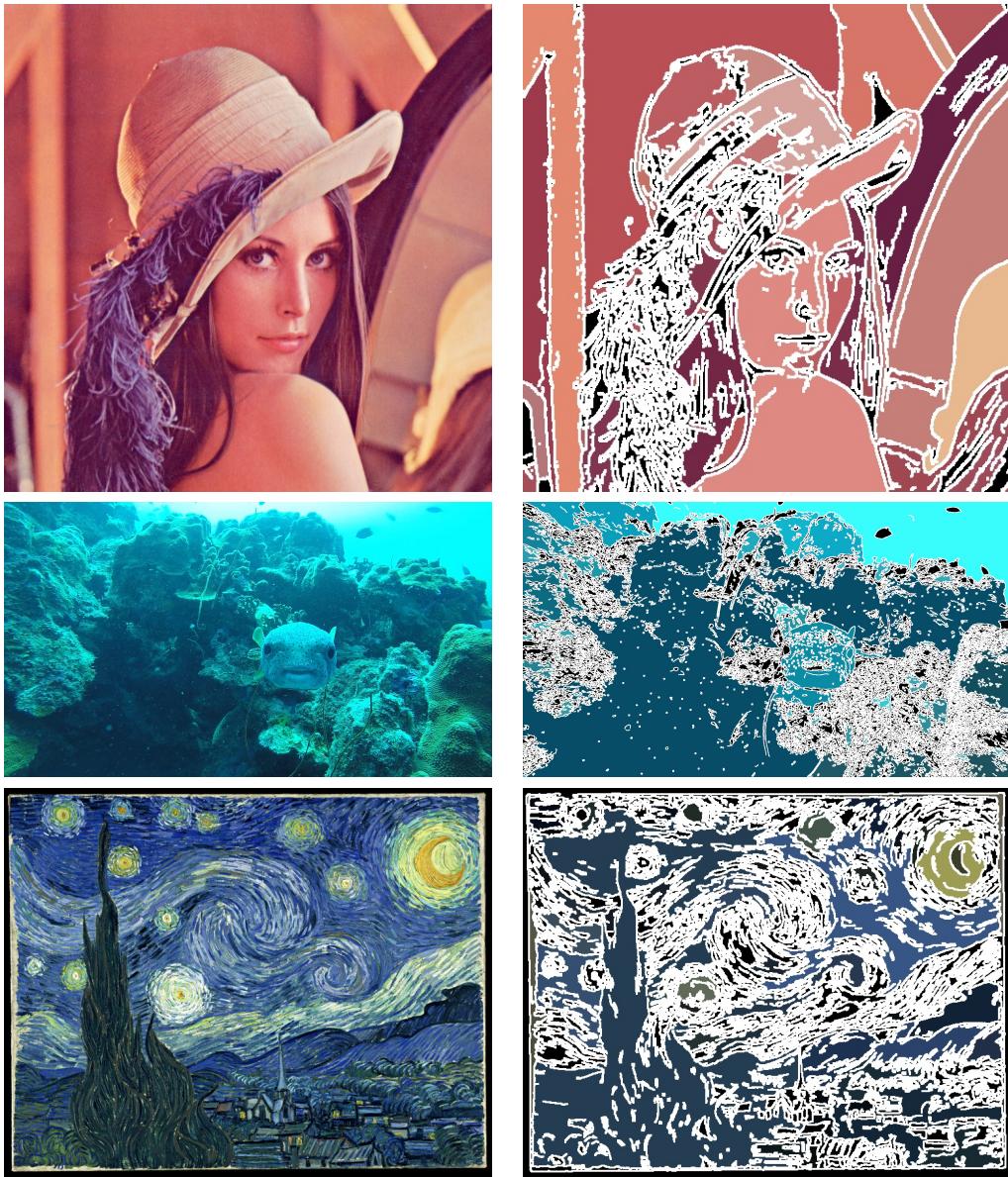


FIGURE A.2: Additional examples of the full abstraction process. The top image (provided by OpenCV) is very simple, so the abstraction gives clean and easily recognisable results. The middle image (provided by fellow student Tom Darlison) was selected due to its limited colour palette and poor focus to test the limits of the process. While the image has mostly filled to a single colour, the pufferfish, rocks, coral, background fish, and open water are all identifiable. The bottom image (provided by OpenCV) was selected due to the extreme number of edges, due to the very clear brush strokes. Once the Canny threshold was turned down considerably, the result was recognisable as Starry Night, though much of the image has been overwhelmed by the edge detection lines. It can be concluded from these tests that the data abstraction process is effective at producing recognisable images, however the difficulty in interpreting the abstracted images is heavily dependant on the focus and complexity of the image.

Appendix B

Contour Based Seed Point Location

The ideal place to aim to flood fill a space from would be the centre point of the space. OpenCV provides the functionality to take the Canny output image (a matrix of colour values) and convert it into a set of contours. Contours are line objects stored in a hierarchical structure and have functions that can provide the centre point of each contour. Although the centre points of the contours will not map exactly to the centre points of the space, they are close enough approximations to flood fill from (Figure B.1).

Unfortunately, due to a combination of the processing time required to convert the lines into contours and the number of contours produced that have no impact on the spaces left to be flood filled, this method is too resource heavy to produce 10 fps on a laptop, therefore is also too resource heavy for use on the raspberry pi.

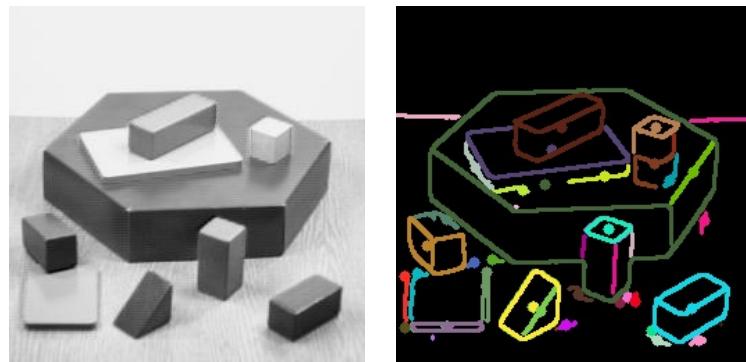


FIGURE B.1: Demonstration of contour centre point location. The original image (provided by OpenCV) on the left has been Canny edge detected, these edges have converted into contours, and the centre points of these contours located. The results of this are displayed on the right, with each contour and its corresponding centre point in a different colour. It can be observed that the centre points provide adequate coverage of the black spaces in the image to be used as seed points for flood filling.

Appendix C

Images of Algorithm Performance Test Scenes



FIGURE C.1: Images of Algorithm Performance Test Scenes. From top to bottom, these are images of the simple scene, medium scene, and complex scene.

Appendix D

Rover Hardware Breakdown

Appendix E

Vectorization

Appendix F

Project Brief

Using Data Abstraction and Inter-Frame Interpolation for Low Data Rate Communication Between a 3D Camera and VR Headset

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There are many challenges, such as monitoring hostile environments, that call for the use of remotely controlled robots. Often in these scenarios, it would be useful to be able to view the environment with a sense of depth to better understand the scale, and dangers, of the robots surroundings. This can be provided through the use of a 3D camera on the robot and Virtual Reality (VR) goggles, however due to the minimum frame rate that can be displayed in a VR headset without causing motion sickness in the user being 60fps (optimally 90fps is preferable), a comfortable and useful experience would often require an unfeasibly high wireless data rate.

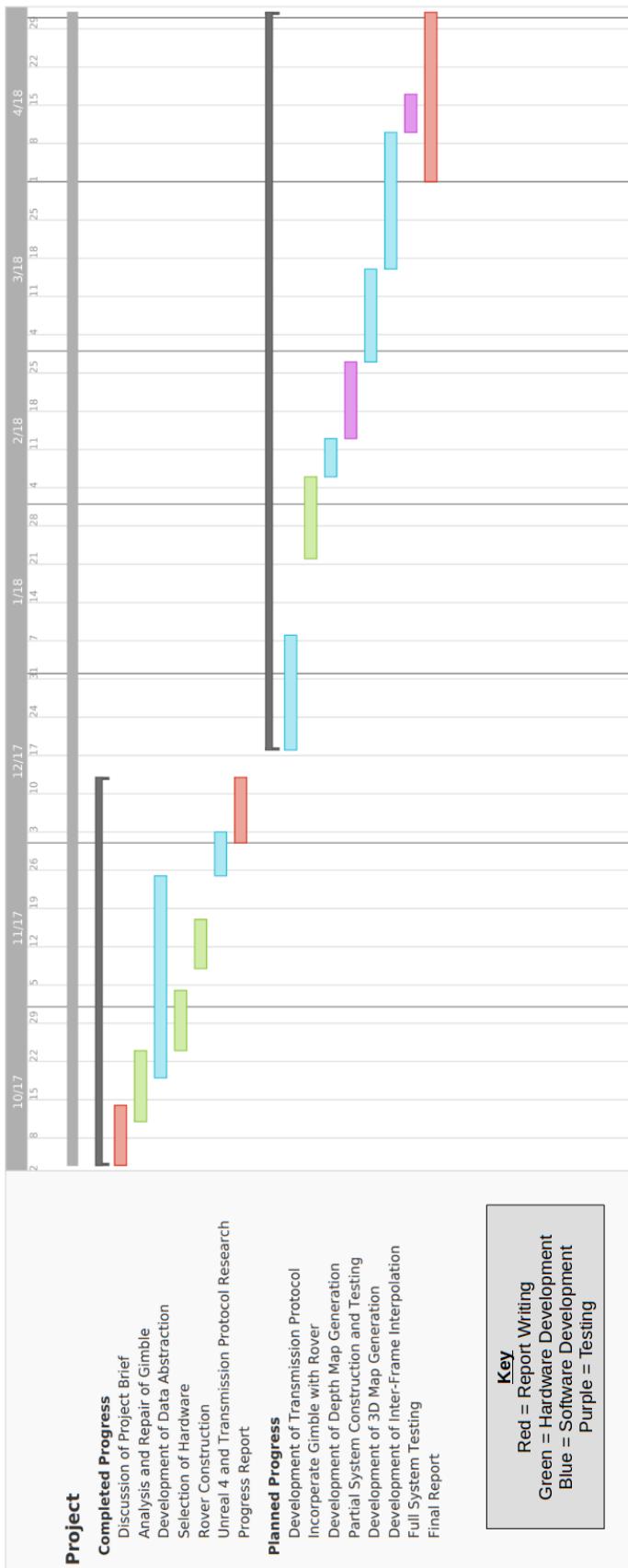
The aim of this project is to significantly reduce the data rate required to be transmitted between a robot and teleoperator through the use of data abstraction and inter-frame interpolation. A 3D camera rig mounted on a remotely controlled rover is to take around 10 pictures per second, then they are reduced down to the minimum amount of data required to identify the objects in the environment. These much smaller images are sent wirelessly to a server, where they are used to create a 3D map of the environment. These 3D maps are analysed and intermediate frames are estimated to increase the frame rate from 10fps to 60-90fps. This much higher frame

rate estimated map of the environment can then be displayed in the VR headset through the use of a video game engine. Although the estimated frames will not accurately represent the real world, the comfort they provide the user will allow them to focus on the transmitted information without feeling ill.

A simple rover and off-the-shelf VR equipment will be used as a foundation for the system. Different camera systems and interpolation algorithms will be tested on this foundation to discern the setup that produces the best ratio between data rate and usability.

Appendix G

Gantt Charts



Appendix H

Risk Assessment

Risk Event	Likelihood (1-5)	Impact (1-5)	Risk Exposure (1-25)	Action
Unable to complete system in time	4	4	16	System is built from the input to the output, allowing for the submission of the working section instead
Response time of the system is unacceptable for use in VR	3	5	15	System is designed and being build with runtime performance as the highest priority
Inter-frame interpolation does not perform as intended	3	3	9	System can function without this component
Data abstraction process is not accurate enough to form a depth map from	2	4	8	Areas where refinement is possible are known so the process can be made more accurate if necessary
EasyCap devices are never available or do not work with the Raspberry Pi	4	2	8	Preparations have been made to use my supervisor's budget to replace FPV cameras with webcams
Data abstraction process is too resource intensive for the Raspberry Pi	2	3	6	Areas where quality reductions could be made in exchange for performance are known
LiPo battery combusts	1	4	4	LiPo batteries are supervised while charging, charged in a flame-retardant bag, and only connected in parallel when the same voltage
Hardware failure	1	2	2	Remaining budget can be used to replace failed component

FIGURE H.1: Risk Assessment for the project going forward.

Appendix I

Design Archive Contents