Investigate feasibility of utilising a neural-networked set of Inertial Measurement Units to compensate for variations in motion of a COTS RC vehicle in a dryland agricultural context.

A thesis

submitted in partial fulfilment

of the requirements for the Degree of

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by

Brett Malcolm Davidson

Lincoln University

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Abstract of a thesis submitted in partial fulfilment of the

requirements for the Degree of Master of Applied Science.

Abstract

Investigate feasibility of utilising a neural-networked set of Inertial Measurement Units to compensate for variations in motion of a COTS RC vehicle in a dryland agricultural context.

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This project explores whether using a neural network of multiple Inertial Measurement Units (IMUs) reduces errors and enhances performance compared to a single IMU in the context of stabilising a video feed of a consumer-level camera on a moving commercial off-the-shelf radio control vehicle. Image stabilisation is desired for efficient identification of objects in the path of a vehicle. The gyroscope of an IMU has inherent “drift” errors as integration of a sequence if frames is required to compute the angles of shift which can then be remedied by a translation matrix. The accelerometer of an IMU is more accurate but is slower which reduces detection time. Kalman filters are often used to reduce noise and other gaussian-based errors but these are computationally heavy for the sort of lightweight processor that a radio control car could be expected to power. A complementary filter is a simpler and less processor-intensive solution and has been explored in unattended aerial vehicles where a pre-determined gain factor is used to combine the gyroscope and accelerometer values.

**Keywords:** IMU, image stabilisation, neural network, translational sensor drift.

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Declaration

I declare that this thesis was composed by myself, that the work contained herein is  
my own except where explicitly stated otherwise in the text, and that this work has not  
been submitted for any other degree or professional qualification except as specified.

*(Brett Davidson)*

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# Introduction

## Motivation

This chapter outlines the requirements around obtaining animal information on a New Zealand farm in a timely and cost-effective manner and a broad discussion of possible solutions for readers not familiar with New Zealand animal data management. The chapter discusses the types of data often recorded and methods of delivering that data back to the farmer. Where an unattended vehicle (UAV or Rover) is suitable, various obstacle detection methods are discussed (including choices of sensors) and an overview of camera-based avoidance techniques is presented.  
The issue of image stabilisation when using camera-based systems and common techniques for mitigating this is discussed.

### NZ Farm information and desired data

To maintain animal welfare and to obtain the best possible profit, beef cattle farmers in rural New Zealand need to acquire accurate and timely data on the state of their livestock. (Dave Swain, Daniel Gregg et al., 2013) In New Zealand, 80% of beef production is exported and international importers wish to purchase pasture-fed healthy beef. (Beef and Lamb NZ, 2017)  
The total area of New Zealand comprises 26.8 million hectares with approximately three quarters of this area above 200 metres in altitude. In 2017, 8.765 million hectares were used for beef and sheep farming spread across 23,403 holdings, averaging 374.5 hectares per farm. 92% of these commercial sheep and beef farms were owner-operated and most farmers farm both sheep and beef cattle as these are complementary for pasture management. In 2020, these farms hosted 26 million sheep and 3.9 million beef cattle, averaging 1,110 sheep and 166 beef cattle per farm. The average figures are somewhat skewed as approximately 45% of the total stock are on farms holding more than 500 cattle. (Beef & Lamb NZ, 2021)

Examples of the type of data collected on a particular animal might include animal movement (to determine most visited feeding and watering areas and to track cattle movement in case of disease), weight, as this is the main measurement used to determine price, along with animal health and fat percentage. Monitoring of farm and pasture conditions (weather, pasture quality, water quality, feed and water levels, images, etc) is also desirable as these have an impact on cattle quality. (Dave Swain, Daniel Gregg et al., 2013) Due to the higher value of cattle versus sheep, sensors are normally only implemented on cattle. (Beef and Lamb NZ, 2017) Optionally, data on the activity of each animal (often obtained by accelerometers around the animal’s neck) could be used to determine if an animal is in distress compared to resting or sleeping. (Derek W. Bailey, Mark G. Trotter, Colt W. Knight, 2018)

<TBC>SETUP THE RESEARCH PROBLEM HERE then describe what follows so that the reader understands why the info that is presented is here.

### Data Gathering Methods - GPS

To track animal movement, a Global Positioning System or GPS sensor with data logging can be attached to the animal. (Y Ropert-Coudert, 2005) To gather weight statistics, the animal must walk over some form of weight scale or via estimation (hoisting an animal to weigh it is impractical). (Wangchuk et al., 2017) Gathering weighbridge data where a farmer is not present to ensure the animal stays still (to ensure an accurate measurement) may introduce errors but this project will not explore these further.   
Once the data is collected it must be transmitted to the farmer. There are three main methods available.

Data Gathering Methods - Radio frequency An RF implementation where satellite (De Sanctis et al., 2016) , cellular service (Gaddam & Rai, 2018) , dedicated radio links (Andreev et al., 2015), LongRange Wireless Area Network (LoRaWAN) (Adelantado et al., 2017; P. S. Cheong et al., 2017; Haxhibeqiri et al., 2018b; Lavric & Popa, 2018),Wifi-Halo (Tian et al., 2021), Bluetooth (Gomez et al., 2012; Team, 2019), ZigBee (Baronti, P Pillai, P Chook, V.W.C Chessa, S Gotta, A Hu, 2007; Gheorghiu & Iordache, 2018) or similar (listed in order of greatest range) (Al-Sarawi et al., 2017) transmit the signals from the sensors to either a central location (this design is called “hub and spoke”) or in a form of mesh where sensors transmit via other sensors until they are in range of the farmer. (Sethi & Sarangi, 2017) Beef cattle are generally farmed in hill country so a direct line of sight from a sensor on the animal to a central radio (or satellite) point is not always possible. (Spark NZ, 2022; Starlink, 2022) Animals tend to travel in groups so a mesh configuration is not practical and would be cost-prohibitive over the distances involved. (Ramseyer et al., 2009).

RF techniques can be split into two types; long range (backhaul) or short range.

#### Long Range or BackHaul

1a. Satellite systems need clear line of sight to 4 satellites greater than 15 degrees above the horizontal plane for GPS but data communication can be achieved with one satellite. While GPS is a free service, satellite data is expensive, location-restrained, power-hungry and generally slow although companies such as Iridium are improving their 1.4kbs links to 512kbs and StarLink has recently expanded its operations in New Zealand with promises of greater than 50Mb/s upload speeds. Starlink as of writing costs $370 to install and $160 per month and has extensive coverage. (Starlink, 2023) The main advantage of using Satellite communications is that the architecture can be flattened to just IoT sensors and a back-end infrastructure, which aids simplicity. Disadvantages are that GPS tracking generally requires a collar or ear tag, which can either end up facing away from the satellite and/or be damaged/removed, etc. and that each IoT device would need to consider robust security measures to ensure confidentiality. There have been significant advances in GPS tracking technology, spurred by avian research (Bouten et al., 2013) that detail how daily GPS location data can be transferred over radio (ZigBee in the study cited) with good efficiencies, however, so using GPS tracking but communicating this data via other more power-efficient communication options, is a very viable solution.  
  
1b. Cellular technologies (2G, 3G, 4G). Public cellular technology support in the high country is sparse. 4G is possible in rural high country but there are pockets of no coverage from commercial providers. (Spark, 2021; Vodafone, 2021). Coverage would need to be evaluated and confirmed on each site.  
Purchasing a SIM card for each animal would quickly become expensive, even without considering damage, but like GPS data, does collapse the architecture down to IoT devices and the cloud.  
It is possible to utilize generic SIM technology to perform connectivity but the customer would be paying for voice capability where that is not required.  
  
1c. 5G Cellular Technologies (Cat-M1, LTE-M, Narrowband-IoT). 5G chipsets are cheaper than 4G chips but due to limited demand, costs are still somewhat high. This will most likely change as demand increases.   
Cat-M1 operates at 1.4 MHz bandwidth and this wider bandwidth allows Cat-M1 to achieve very good data rates (up to 1 Mbps – generally 200-400kbs) with low latency and device positioning capabilities. Cat-M1 supports voice calls and connected mode mobility. Cat-M1 generally has a similar range as 3G and 4G (10-15km) since it extends the same LTE-based cellular technology underpinning these.   
LTE-M is a competitive system to Cat-M1 with similar features.  
Narrowband-IoT (NbIoT) sacrifices throughput (250kbs maximum upload with a payload size of up to 1600 bytes) for extended range and improved power usage.   
All 5G technologies mentioned here can support more than 55,000 simultaneous clients.   
Differentiating Cat-M1, NB-IoT and GSM-IoT.
Source: 

Figure 1‑1 Differentiating Cat-M1 and NB-IoT technologies. Image from (*Standards for the IoT*, 2016)

1d. WiMAX (WorldwIde operability over MicrowAve) is a technology using Microwave links.  
WiMAX does not require line of sight to operate and has further range than conventional Wifi (30-50km maximum limit for line of sight). Power usage is very good compared to cellular networks (Deruyck et al., 2010). There are two main types of WiMAX; fixed and mobile and these are very different in infrastructure. There are few public WiMAX deployments in NZ and none in rural spaces so the farmer would need to invest in WiMAX infrastructure and deploy stations in the appropriate places to get coverage to and from the remote areas. Wimax appears to be losing the battle for spectrum to cellular providers and a “recent” (2017) spectrum analysis report indicates there is little intention for WiMAX to be implemented in a large scale in NZ (New Zealand IoT Alliance, 2019). As such, for futureproofing rationales, WiMAX Is not recommended for use.   
  
1e. SigFox. SigFox is a proprietary system where IoT devices connect to base stations which connect to each other via point-point links (max of 50km range) back to the SigFox cloud. Each sensor can report up to 12 bytes in a message (26 bytes in a frame), with a maximum of 140 messages per day. Transmission speed is either 100 or 600 bits per second (SigFox, 2023b).  
Coverage of some areas in New Zealand is suggested at Sigfox’s commercial website (SigFox, 2023a) however both the proprietary nature of SigFox and it’s low transmission rates, make it unappealing as a solution, and SigFox is not recommended for use.  
  
1f. Lora is a competitor to SigFox. This is a low power communications protocol designed to send small packets of data at regular intervals with low-power usage. It’s a proprietary protocol owned by Semtech. (*What Is LoRaWAN® | LoRa Alliance®*, n.d.)LoRaWAN is an open source point to multipoint messaging protocol built to utilise the Lora communications protocol. (*What Is LoRaWAN® | LoRa Alliance®*, n.d.)   
LoraWAN has very low power requirements and a practical range of up to 3km in an urban environment (Augustin et al., 2016) and up to 15km in an rural environment (Haxhibeqiri et al., 2018a) but has a duty cycle limit (1% duty equals 36 seconds of communications time per hour for each device). It prefers line-of-sight communication to perform well. (Haxhibeqiri et al., 2018a). Transmission speed varies from 300bps to 37.5kbps with a maximum payload of 246 bytes.   
The theoretical maximum nodes in a Lora system are 10,000 but LoraWAN has scaling issues of a maximum of 8,000 devices (1000 nodes per channel with 8 channels) at a collision rate of 95% (Lavric & Popa, 2018). More stations are required in order to alleviate this, which is possible as LoraWAN operates in a star of stars fashion where every station receives the transmissions of all devices around it.

In NZ, there are two widespread public LoraWan deployments but in many sites, the farmer would need to invest in LoraWan infrastructure and deploy stations in the appropriate places to get coverage to and from the back-end stations.   
There are no fees at present for operating LoraWan systems but a license is required. (*Short Range Devices GURL | Radio Spectrum Management New Zealand*, n.d.)  
Each LoraWan edge station requires a TCP/IP-based backhaul protocol to deliver content to the cloud. This could be possible within an area covered by one of the 5G protocols.

1g. Dedicated radio links utilising microwave transmissions are a possible solution but the frequencies used are not generally available for the general public and would require specific designs for each station. Annual licensing costs also apply (*Fixed Link Licence | Radio Spectrum Management New Zealand*, n.d.) Depending on the distances it might be more cost-effective to implement direct links but this technology implementation would be site-specific and costly, and will not be evaluated in this review.

Table 1.1 Backhaul (long range) communication protocols compared.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Protocol | 4G | Cat-M1/LTE-M | NbIoT | LoraWan |
| Standard |  | 3GPP LTE CatNB1 | 3GPP LTE CatNB2 | IEEE 802.15.4g |
| Frequency | Licensed | Licenced | Licensed | 915 MHz |
| Range | 10 km | 10 km | 12 km | 5 km |
| Transfer Rate | 2 Mbps | 300-400 kbs | 20-127 kbs | 50 kbs |
| Power usage | 250 mW | 220 mW | 200 mW | 125 mW |
| # clients | 55,000 | 55,000 | 55,000 | 10,000 |
| Availability | Very high | Very high | Very high | Limited |
| Major Limitations | Range | Data rate Capacity | Range Data rate | Data rate Capacity |
| Applications | Video/Voice required | Images/Voice required | Images required | Small datasets generated hourly. |

#### Short Range

1h. ZigBee or 802.15.4 (Baronti, P Pillai, P Chook, V.W.C Chessa, S Gotta, A Hu, 2007) is a standard for small personal LAN communication with a range from 10-100m for the standard variant and a practical range of 3.9km for the long range Zigbee variant (15km is advertised). (Jawad et al., 2017). Maximum nodes are 65,000 which should be ample for even a large farm. Range limitations can be overcome by using repeaters. ZigBee requires line of sight communication which is a limiting factor but has low power requirements. Transmission rate varies from 20 to 250kbs. Zigbee is designed to support multi-hop networks. There are three types of devices in a Zigbee network; FFD (Fully functional device which can also act like a router), a RFD (Reduced Functionality device) and a single coordinator. Routing traffic is in-band with the data.  
Zigbee is a potential solution provided that the distance between stations does not exceed the line of sight communications range. The main advantage of ZigBee is that it can use bursts which enables the rapid transmission of data however it is a short range protocol and an intermediary device would be needed to communicate data back to the farmer. Some extensions to Zigbee are 6loWPAN (Ietf, 2020) which is essentially Ipv6 over Zigbee, and Thread (Threadgroup, n.d.) which is an attempt to create a universally utilised Home automation protocol over 6loWPAN. There are no 6LoWPAN devices or Thread devices available in NZ as of writing but it is possible to implement the 6loWPAN and Thread protocols over the top of Zigbee devices with firmware updates. Zigbee is a possible solution for communicated between cattle and to a very local transmission site but other devices will be needed to transmit data back to the farmer.  
  
1i. Dash7 (*DASH7 Alliance – An Open Specification*, n.d.) arose from military RFID use and primarily utilises the 433MHz band which gives it multi-km range. To improve performance some network cards support the 868 and 915MHz unlicensed ranges as well. Bandwidth is either 25kHz or 200kHz which gives transfer rates of 9.6kbit/s, 55.55kbit/s or 166.7kbit/s. Max packet size is 256 bytes. (Arsalan et al., 2018). There are no retail providers of Dash7 devices in NZ so this technology is not recommended.

1j. Wifi HaLow is based on the IEEE 802.11ah standard (Shanmuga Sundaram, 2016) and consumes less power than standard wifi with a longer range; up to 750m using the “unlicensed” frequencies from 915-928MHz. (same as Australia and Japan but Japan only supports 1MHz bandwidth). Being a superset of Wifi, Wifi Halow supports IP based communication and is designed to support a lot of simultaneous clients (up to 8191 as 13 bits are used for an ID) in a star-shaped network with data transmission rates from 150kbs to 347Mbs. Up to 6960 stations can be simultaneously connected over 1km while transmitting 100 bytes of data every 60 seconds without packet loss when tuning TIM (12 groups) and RAW (2 slots) parameters. In essence, sending more data in a single packet increases the number of simultaneous stations available with a maximum packet size of 7991 bytes unaggregated or 65535 aggregated bytes. In terms of power efficiency, 802.11ah enables 500 IoT devices to turn on their radios 3% of the time when transmitting every 60 seconds. (Šljivo et al., 2018). Wifi-HaLow is included here despite there being no retail supply of network cards in New Zealand as it has some distinct advantages that may make it worthwhile to source parts from overseas. One of these advantages is the multihop relay support integrated with the technology.

1k. Bluetooth V5 was released as an enhancement for IoT devices. The theoretical range (240m@125kbps) is 2 times that of Bluetooth Low Energy (mentioned below) but requires significantly more rf output power (from 10mW to 100mW). (Team, 2019) The Bluetooth V5 protocol stack supports IP based communication natively which is an advantage. There are four data transfer rates of 2Mbps, 1Mbps, 500kbps and 125kbps, with increased range at each reduction of rate.  
For both power usage and connection speed advantages, Bluetooth is very attractive. Bluetooth 5 also includes mesh networking, making this a significant challenger to ZigBee.  
  
1l. RFID is short range only (less than 2m) but has extremely low power usage. (Duroc, 2022; Jia et al., 2012; Landaluce et al., 2020) RFID tags are required for cattle identification in NZ (NZ Government, 2018) so these tags will be present, regardless of any other technologies chosen (Williams et al., 2019).

Table 1.2 Short range communication protocols compared

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Parameter | RFID | ZigBee std | ZigBee LR | BLE | BT5 | LoraWan | Wifi HaLow |
| Standard | RFID | IEEE 802.15.4 | IEEE 802.15.4 | IEEE 802.15.4 | IEEE 802.15.4 | IEEE 802.15.4g | IEEE 802.11ah |
| Frequency | 433Mhz | 2.4 GHz | 915 MHz | 2.4 GHz | 2.4 GHz | 915 MHz | 915-930 MHz |
| Range | 2m | 60 m | 14km / 6.5km | 10m | 750m | 5km | 1km |
| Data rate | n/a | 250 kbs | 10 / 200 kbs | 1 Mbps | 125kbps-2 Mbps | 50 kbps | 150 kbs (1km range) – 80Mbps |
| Power use |  | 36.9  mW | <250mW | 10 mW | 10 mW | 125 mW | 11mW |
| Network size |  | 65,000 | 65,000 | App-defined | App-defined | 10,000 | 8,191 per AP |
| Network topologies |  | P2p, tree, Star, mesh | P2p, tree, Star, mesh | Star | Star | Star of stars | Star,Relays |
| Native IP |  | No | No | NIC-Specific | NIC-Specific | No | Yes |
| Limitations |  | Line of sight | Power usage | Short range | No mesh support | Data rate, capacity | Limited devices |

Table 1.3 Communication protool options available on a range of microcomputers

Key: I=Inbuilt, M=Module available in NZ,O=Module available from Overseas and X=Not Suitable

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Comms option | Pi V4 | Rock Pro64 | Jetson Nano | Tinker EdgeT | Arduino MegaR3 | Microbit | ESP32 |
| GPS | M | M | M | M | M | O | O |
| 802.11ah | O | O | O | O | O | O | O |
| BT 5 | I | M | M | M | M | X | O |
| BT BLE | M | I | M | I | M | X | I |
| ZigBee Std | M | M | M | M | M | O | O |
| ZigBee LR | M | M | M | M | M | O | O |
| 433MHz | M | M | M | M | M | O | O |
| LoraWan | M | M | M | M | M | M | M |
| NbIOT | M | M | M | O | M | O | O |
| Cat-M1 | M | M | M | O | M | O | O |
| LTE-M | M | M | M | O | M | O | O |

If reliable frequent communication is not possible extra storage may need to be provisioned on the sensor device to act as a data buffer, raising the costs and lowering the battery life of each sensor unit.

### Data Mule method

To avoid the monthly costs and possible infrastructure investments in RF backhaul technology, a travelling device (rather than the actual farmer) could visit the herd, download the data and upload this data on return. This concept is called a “data mule” as the device is purely a carrier for data in a similar manner as the ethernet over avian carrier protocol. (Waitzman, 1990) At the time of writing, this approach would incur significant range limitations and requires efficient pathfinding requirements of the device, along with the requirement that the device distinguish between animals and other obstacles. The device would need to navigate close enough to each animal to read the passively powered RFID sensor information without being trampled and/or startling the animal and obtain data from the other sensors on the animal. Most research on data mules in a rural context has concentrated the use of Unattended Aerial Vehicles (UAV or “drones”) as these significantly reduce the issues involved in efficiently traversing terrain and avoiding obstacles between the various sensor locations. This approach is not feasible at present in New Zealand as the current civil aviation laws in the country prohibit autonomous operation and require an operator to have line-of-sight visibility of a drone at all times (Aviation Authority of New Zealand, 2015). An unmanned ground vehicle (UGV or “rover”) could be utilised however these face the same issues as a drone, with additional route planning and obstacle avoidance problems. A sole data mule option is not addressed in this project.  
  
Beef cattle tend to revisit feed and water lots (Johnstone-Wallace & Kennedy, 1944; Martina et al., 2015) so a hybrid of options One and Two could be implemented where cattle visit a solar-powered data-aggregation feed/water site and transmit their data by one of the low range, low power methods in option 1 (Wifi-Halo, Bluetooth, Zigbee for example) (Jawad et al., 2017) and then, either a dedicated radio link or a data mule device can be used to deliver the data from the aggregation point to the farmer at regular intervals. An advantage of this method is that photographs of animals can be taken when they visit the site to enable a visual inspection of animal health and scales to measure animal weight could also be implemented. Using a dedicated radio/cellular/satellite link to communicate this data back to the farmer will require licensing to be obtained and requires that the data-aggregation site be located where radio connectivity to the central location is feasible. Each site’s infrastructure will need to be repeated for every feed/water site where observations are required. The data will need to be stored for as long as it takes for a communications link to transfer the data or for a data mule to visit the site. It is envisaged that a maximum period of at least once every 24 hours would provide timely data.

### Utilising a rover as a data mule

An unmanned ground vehicle (UGV or “rover” as they are more commonly called) could perform the role of a data mule and potentially provide other benefits such as supplying feed/water to the sites of interest however common issues that arise are ensuring reliability, effective range/battery life, efficient sensor data capture/storage, efficient route planning and obstacle avoidance. (Borges De Sousa & Andrade Gonçalves, 2010; Chemhengcharoen et al., 2019; Manderson & Hunt, 2013; Petterson, 2020).  
  
Reliability and Battery life  
  
Reliability of rovers has historically been low but investigation and potential solutions have mostly been examined in a lab environment (Nguyen-Huu & Titus, 2009). Key factors from this 2009 report showed that rover solutions must be capable of self-examination and repair and introduced the notion of replaceable parts.

Previous rover-based approaches have been based on creating a customised rover from the ground up, most often at a large scale of at least 1:5, ranging up to 1:2 (Borges De Sousa & Andrade Gonçalves, 2010; Chemhengcharoen et al., 2019; Manderson & Hunt, 2013; Petterson, 2020). To the authors knowledge, no research has been undertaken on the use of commercially available, off-the-shelf (COTS) RC models as data mules and an initial pilot system implemented by the author of a 1/10 scale Tamiya “Bruiser” RC car (Tamiya, 2012) proved that this size vehicle is too small to hold the amount of battery packs required to successfully navigate a farm at the current time. A minimum size for a rover was not ascertained in that study but an estimate can be made that at least a 1:5 scale vehicle will be required, which is handy, as that is the largest size of commercial RC cars produced. If a larger model is required, then either a custom design will be required or significant conversion of a small all-terrain vehicle (ATV or “quad-bike”) (Honda Limited, 2023) or similar.  
  
Battery optimisation is crucial to maximise the range of a vehicle and has been well-covered in prior works (Baek et al., 2019; KISHORE et al., 2018; Manderson & Hunt, 2013; Sinclair et al., 1998). In particular, Baek’s battery optimisations (Baek et al., 2019) were used as an input for effective route planning but his approach does not consider obstacle avoidance, and the current battery technology does not permit a small vehicle to carry the batteries necessary to power it, but, with increases in purchases of EV vehicles, battery technology is improving rapidly (Hall, 2021; Zogopoulos, 2021). If the vehicle is large enough, petroleum-based fuels could be utilised to bypass this restriction, however, automatic recharging of an electric system would be preferable, as the operation could then become fully autonomous. Interestingly, Petterson also discovered that tyre selection had a significant impact on range (Petterson, 2020).

#### Route Planning

Effective route planning is an essential feature of a rover. Efficient localisation and path-finding has been widely studied and is generally treated as a standard nondeterministic polynomial or NP-problem (Encyclopedia Brittanica, 2023). Other approaches, such as Sugihara and Gupta (YEAR), have explored this further as an NP-Neighbourhood problem, utilising an approximation LCP algorithm that allows for varying radio frequency ranges at each aggregator using semi-online algorithms (Sugihara & Gupta, 2011). Their approach enables a rover to navigate to within wireless range of a site instead of directly driving to the site’s actual location.   
Before a vehicle can determine where to go, it’s helpful if it knows where it is. Localisation can be divided into pure localisation where the surrounding territory is known (based on maps) or simultaneous localisation and mapping (SLAM) where the vehicle will need to build a map and localise itself within the map. This project is based around a vehicle travelling to known locations so only the pure localisation methods will be mentioned.

##### Localisation

* The main global localisation technique is to use a global positioning system (GPS) sensor which performs triangulation from signals received from multiple global navigation satellite system (GNSS) to determine location.

Relative localisation implementations determine their position by gathering sensor data relative to the vehicle and/or to a known initial position. The main approachs are:

* Dead reckoning is a technique where integrating wheel revolutions, steering angles and speed will provide an estimate of location. Errors accumulate over time, epecially if there is wheel slippage or high inaccuracy in the data used to estimate. This method is not recommended for use.
* Inertial sensors such as accelerometers and gyroscopes can be used and their values integrated to provide position and heading information. Magnetometers can directly provide headings if there are no sources of metal nearby to intefere with the readings. This approach suffers from accumulated errors as there is drift from the use of integration as will be demonstrated in Section 2.
* Visual odometry processes camera images and compares the relative transformations between successive images to estimate trajectory. The process largely involves transformative matrices and geometry and will be explored in more detail in Section 2.
* Radio detection and ranging (radar) and Light detection and ranging (lidar) (Byeon & Yoon, 2020; Goodin et al., 2019; Wallace et al., 2020) sensors are more accurate than cameras but are more expensive and in the case of lidar, usually only gather data in a single plane, requiring further processing. The precision of these sensors is not required for this project and these will not be evaluated.

##### Map formats

Once the vehicle knows where it is and knows where it needs to go, it needs to work out how to get from one to the other. Before planning commences, the format of the map (and obstacles) the vehicle will encounter needs to be determined. The main types are:

* Cell Decomposition methods. The map space is decomposed into a set of discrete, non-overlapping, adjacent cells. These cells can be used to formulate a path of cells between the start and end points. Cells can be full, partially full or empty of obstacles. Depending on the detail required, the full set of cells could require substantial memory. Adaptive cells reduce the cell size where the topology is not likely to contain any obstacles to save memory but if new obstacles appear the map will need to be completely recalculated. Variable sized cells are difficult to apply in a rural environment.

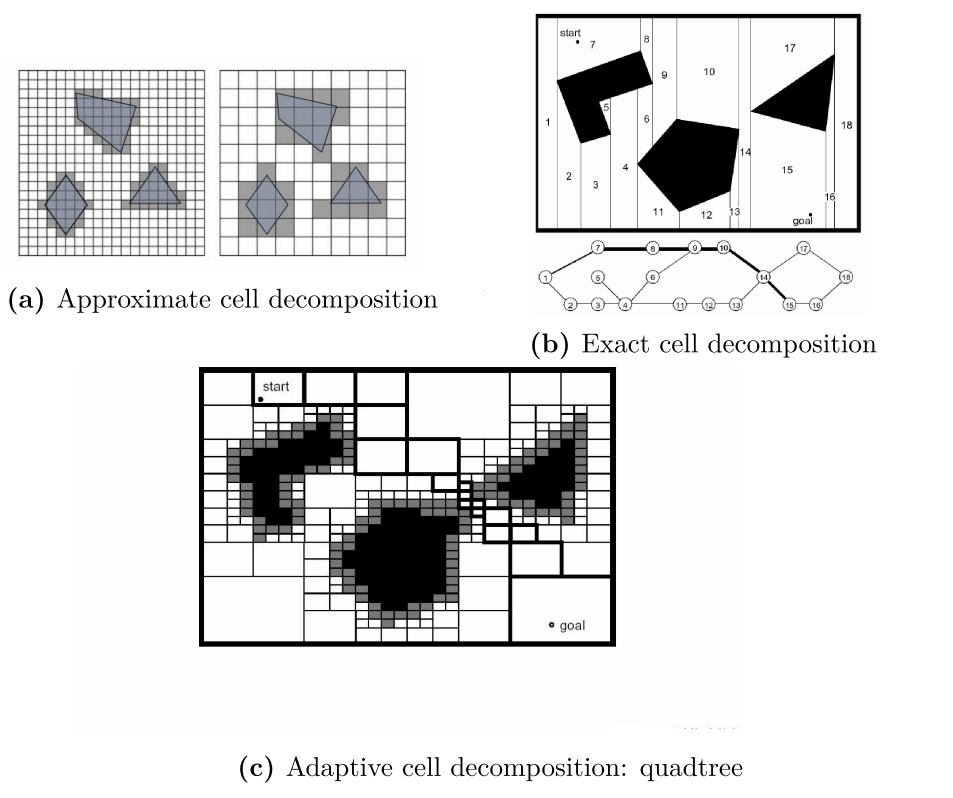


Figure 1‑2 Cell Decomposition examples. Image from (Chiaberge, 2020)

* Roadmap methods utilise graph structures where connections between free space regions are built as a set of one-dimensional curves. The nodes used in the curves are usually created using distinctive locations but this requires careful selection and recalculation of the entire map as new sensor data arrives. Main types of roadmap methods are
  + Visibility graphs where the curves are represented by straight lines, connecting the selected nodes. Careful selection of region size is required to avoid the vehicle hitting an obstacle (these are normally defined using polygons where nature favours round or amorphous shapes) while traversing versus an inefficient path. There are a few types of these:
  + Voronoi diagrams consist of a set of paths (edges) which are equidistanct for all points within the obstacle area. They are built as far from possible from obstacles so the generated paths are safe but inefficient. <TBC>
  + Probalistic Roadmaps or PRM is a discrete implementation of a continous map, generated by randomly sampling the entire map and connecting the sampled points into a roadmap with straight lines, the theory being that a small number of points and paths are normally sufficient to represent connectivity of free space regions. PRM first builds a roadmap and iteratively removes connections where connecting lines intersect an obstacle location. PRM then queries the built roadmap for the path of least-cost. The roadmap generation is slow but once generated, the path mapping is very efficient.
  + Rapidly Exploring Random Trees or RRT is a variation of PRM where the points are chosen randomly and expand a tree that represents a path. RRT is useful for dynamically changing or non-holonomic maps.

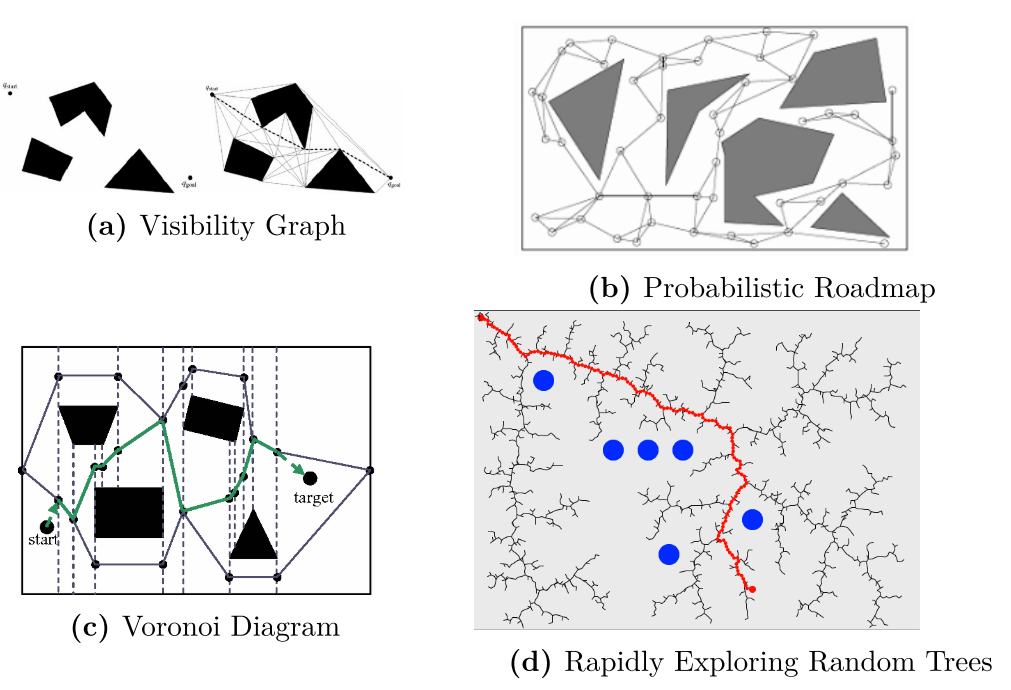


Figure 1‑3 Examples of Roadmap methods. Image from (Chiaberge, 2020)

* Potential fields impose a mathematical function over the entire map which maps free space as an attractive forces and obstacles as a repulsive force. It was originally designed for real-time obstacle avoidance but is also a useful path-planning tool. The main penalty of the technique is the presence of local minima points different than the goal, causing the vehicle to get stuck.

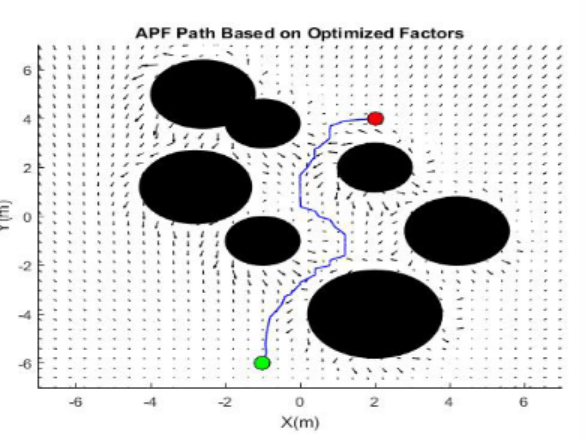


Figure 1‑4 Potential Field algorithm example. Image from (Raheem & M.Badr, 2017)

##### Path Planning

There are two main aspects of path planning.  
Global planning occurs where the path is developed from knowledge already known about the environment. Local planning occurs where the rover will need to respond to detected obstacles or topology changes since the global map was developed.  
There are two main algorithm approaches used in global path planning; heuristic or artificial intelligence (AI). Below are outlined five of the common heuristic variants.

* The Dijkstra algorithm (H. Wang et al., 2011) is not acutally heuristic but is the basis for many of the other algorithms. It divides the territory into a segmented graph where the edges of each segment contain weights relating to their cost. The efficiency of this algorithm is low as it traverses almost all graph segments (nodes) to determine the best path.
* The A\* algorithm (University, 2020) is based off the Dijkstra method but uses heuristics to adjust the cost of traversing between nodes – essentially it prioritises routes that lead towards the target which is more efficient, despite the additional costs of processing the heuristic function. There are a few variants of this approach such as life long planning A\* (LPA\*). (Koenig et al., 2004). Li et al built a camera-IMU integrated view along with a segmentation structure to determine 3D landmarks and then use this with the A\* algorithm (University, 2020) to perform path planning in an urban environment. They only evaluated this approach in simulation and advised that a deep learning network and improved pose algorithms should be implemented in scenarios of highly dynamic obstacles.
* Another variant of A\* is D\* which stands for Dynamic A\*. (Ferguson & Stentz, 2006) The original D\* is an incremental search algorithm where the costs can change while the algorithm runs, permitting fast map updates if the number of obstacles changes dynamically.
* The focussed D\* is a combination of A\* and D\*.
* D\* Lite is a combination of D\* and Life Long Planning A\* (LPA\*).

Artifical intelligence path-planning algorithms incorporate three main approaches:

* Genetic Algorithm or GA (Lamini et al., 2018) is a simple approach where all possible solutions are encoded as “chromosomes” and biological evolution processes such as mutation and selection are applied in order to determine the best outcome. It is efficient but is prone to premature convergence.
* Ant Colony Optimisation (ACO) uses the concept that ants leave pheromones (weights) where they travel so that following ants will be attracted to travel this path as well.
* Particle swarm optimisation or PCO (Ab Wahab et al., 2015) utilises group behaviour by iterating through each selection, comparing each against global criteria until the optimum is found. Mohanty and Dewang (Mohanty & Dewang, 2021) used APSO, which combines A\* and PSO as a method for path planning but only evaluated on a flat topology and with a simple obstacle patterns.

Local path planning is used where the vehicle needs to react to an environment that was not predicted or otherwise different than the global map. The process can be divided into five categories.

* Artificial Potential Field which is a variation of the Potential Field algorithm outlined earlier.
* The Behaviour decomposition method breaks down navigation into a set of primitives such as collision avoidance, tracking, planning, etc. which coordinate with each other to achieve the overall navigation task.
* In Case based learning the vehicle builds a database and when it finds a new problem, it searches the database for a similar problem, compares and analyses the results to find a solution.
* With the Rolling Windows algorithm, the system recursively calculates a suitable window based on the environment. Real-time planning is implemented using sub-targets in a similar fashion to behavious decomposition. Each subtarget output is computed byu heuristic methods and are updated each time the rolling window moves, until the planning task completes.
* Artificial Intelligence solutions are the same as previously discussed.

Masehian’s and Katebi’s approach (Masehian & Katebi, 2014) used a rangefinder and took two timed measurements to determine obstacle speed so as to avoid the object while still navigating to a moving target. They employed a concept they called directive circle to give a “pie-chart” view of which areas were safe to travel based on the centre of the rover, allowing for width of the rover and the rover’s turning circle. They did not test the model in the field and the algorithm predicts object movement based on history rather than prediction.   
  
As can be seen, the selection of obstacle avoidance methods has a considerable impact on the viability of rural route planning.

### Obstacle Avoidance

As a rover traverses the terrain, it is essential that it avoids objects that could cause damage to itself and/or vegetation. Animal (including human) object avoidance is paramount. Despite considerable research into rover obstacle avoidance

#### Obstacle Types

Obstacles can be defined as either static (fixed location) or dynamic (mobile).   
Many obstacle-avoidance systems treat all objects as dynamic objects, a safe default, but this approach requires significant processing power and prevents a rover from passing these objects closer than it might otherwise, reducing rover range.   
Where systems do distinguish between static and dynamic obstacles, this is often determined when these are scanned (is the object moving right now?) which offers little processing benefit over the purely dynamic approach. Static objects can be predefined before the rover ventures on its run when an aerial map is loaded to form an initial route, but a map may not identify all objects.  
Classifying obstacles via a static map loaded at initialisation on site and classifying obstacles and updating this map as the robot passes each object would provide the best efficiencies.  
  
To avoid an object we need to know what types of obstacle are expected and how to identify them.  
The nature of rural obstacles will depend on the topology of the farm, but in New Zealand, will likely comprise of:  
1. Various vegation types of various lengths, some of which may be considerably taller than the rover, along with trees and shrubs at various stages of growth.  
2. Various soil types, ranging from very sandy to extremely clay-heavy, which retain water differently, so the rover must be able to distinguish between dry or boggy conditions and ideally differentiate between deep and low-lying pools of water.  
3. Rocks and stones, which are numerous on NZ farms and the rover must decide to either climb or circumnavigate these obstacles.  
4. Various weather conditions - sun, snow, rain, ice and fog.   
5. The terrain gradient which needs to be traversible or avoided.   
6. Rabbit warren holes and/or other large depressions which need to be avoided.  
7. Farm fencing, where the rover must either stay within the defined boundary and/or detect and utilise methods to pass through fences, gates, cattle stops, etc.  
8. Humans, animals and any farm equipment, which must be avoided, wherever they are.‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬

#### Typical Obstacle-detection sensors

Sensor classification falls broadly under two functional axes: proprioceptive/exteroceptive and passive/active. (Siegwart et al., 2011)  
Proprioceptive sensors detect the rover’s state such as position, orientation and speed via velocity sensors (W. H. Zhu & Lamarche, 2007), inclinometers/gyroscopes (Dai et al., 1996) , position sensors (Chao et al., 2013), heading sensors or accelerometers (Beliveau et al., 1999), etc.  
Exteroceptive sensors collect information from the environment around the rover via such sensors as time-of-flight (Foix et al., 2011), lidar (Yan et al., 2015), laser (Suh, 2019), sonar (Choit et al., 2005), microwave radar (C. Li et al., 2017), and cameras (Bernini et al., 2014).  
The other axis delineates between passive and active sensors.  
A passsive sensor such as a CCD camera (Fossum & Hondongwa, 2014) or thermal camera (Akagawa, 1996) receives environmental information energy whereas an active sensor generates and emits energy and measures the response. Passive sensors use less power but often require more processing time to process resulting datasets.  
Active sensors tend to require less processing time and have further range but require power to emit the signals and can be influenced by other sources of similar energy.  
  
Diagram

Description automatically generated

Figure 1‑5 Sensor Types

Radio detection and ranging or “Radar” is an active system often utilised on full-size vehicles as it has a long range and can cope with dusty conditions. The system works by emitting radio signals and timing how long it takes for the signal to return after being bounced off an obstacle. Rain and snow can cause attenuation, but in a large vehicle, power may be boosted to compensate for this. The data returned is of high resolution (normally a point) but categorisation of an object is not possible without further processing.

Forward looking UWB (ultra-wide-band) radar can penetrate grasses (Wong et al., 2003) to determine rocks hidden behind tall grass, etc. but developing a data model for the reflected nature of holes such as rabbit warrens may be indistinguishable from background noise and may not measure far enough ahead of the rover for the rover to be able to avoid the obstacle. This is an aspect of object avoidance that does not appear to be well-researched‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬ besides Wong’s work but is a project more suited to an RF engineer to design the required antennae array and is out of scope for this project.  
  
Sonic navigation and ranging or “Sonar” (typically an active ultrasonic sensor) works like radar but the systems emits sound rather than radio waves. Sonar suffers from environmental constraints such as wind, temperature and humidity which effect the measurement accuracy (Mohammed et al., 2020). Ultrasonic sensors are also limited to the speed of sound (the signal attenuates heavily in air) and thus have limitations on their range. The wavelength is approximately 4mm and so can miss some narrow surfaces such as a narrow bush branch, etc. As sonar uses reflection, like radar, any surfaces at oblique angles (soft edges) to the rover may not reflect back (Mubarak, 2013) and reflections from multiple objects may also confuse a sensor. Vegetation tends to confuse a sonar system as well, particularly if the grass is blowing in a wind. The wide beam angle reduces directional resolution (overlapping ultrasonic sensors have been used to reduce this limit) and the speed of sound (343m/s) limits the sensing rate. (Kleeman & Kuc, 2008). Sonar’s main advantages are price and that, being sound based, they are immune to visibility issues such as dust, fog and night.  
  
Light detection and ranging or “Lidar” has been used effectively in many rover deployments and is the method of choice for many household vacuum cleaner robots (Mohammed et al., 2020). Lidar is an active light (light amplification by stimulated emission of radiation or “laser”) reflection system and is less affected by background solar radiation or night but is affected by dust, fog, rain, ice and snow (Formsma et al., 2010). 360degree lidars are a relatively cheap form of object detection, enabling edge detection of an object, but only scan in a single dimension, missing objects higher or lower than the narrow scan angle. Scanning vertically while a motor rotates the lidar unit provides a complete viewpoint but reduces scanning time, limiting predictive ability. Wind effects on grass may also confuse the sensor. Maximum range is about 80m with an accuracy of +/- 50mm over a range of 20m (Crane et al., 2006) but consumer-level lidar units tend to have a range of 12m. (Adafruit, 2022)  
  
Far-infra-red passive camera sensors have long range and are immune to most environmental factors such as rain, snow, etc. and provide improved resolution at night. They suffer from high cost and moderately high computer processing power required to analyse the visual data, along with low resolution (compared to a conventional camera) and only produce grey-scale images. Distinguishing objects in cold environments may be difficult. (Mohammed et al., 2020). Matthies and Rankin (L. Matthies & Rankin, 2003) found that thermal signatures are effective at determining depressions and other holes in the ground, although their approach worked best at night and would need to take solar radiation into account for daylight use. Other Infra-red systems (tyically active systems) are more effected by environmental conditions, especially solar radiation from the sun.

Passive camera systems can be used as rangefinders (Druzhkov & Kustikova, 2016; Gao et al., 2016; S. Huang et al., 2020; Mohammed et al., 2020; Moravec, n.d.; Rajavarshini et al., 2021; Schäfer et al., 2005). Backlighting and lens flare are the main issues with using cameras besides their limitation of daylight-only use, without additional lighting.  
Monocular cameras use the size and shape difference between succesive shots to determine depth and can be confused by areas of sharp contrast, especially shade in a bright sun. (Michels, 2005).   
Stereo cameras can have better noise immunity and these are easier to derive range information from (via triangulation from the two cameras) but processing two sets of images requires more computing power.  
Schäfer, etc. implemented a “depth discontinuity” method to determine obstacles above and below ground level using a stereo camera, recognising that traditional ground level references do not apply in a typical outdoor topology. (Schäfer et al., 2005). The weakness of this approach is that the camera needed to be angled towards the ground, and thus there is a contradictory relationship between angle, the size of the obstacle that can be determined, and rover speed, which was not explored in their work. It also means that the camera may have limited forward vision, depending on the angle, which may require additional sensors to address.  
Sharma and Shah used image processing to determine if animals were present with an 82.5% accuracy (S. U. Sharma & Shah, 2017) however this required significant processing resources (Corei5) to produce 10 fps images.

Table 1.4 Single obstacle-avoiding Sensor Summary

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Sensor | Radar | Ultrasonic | Lidar | IR | FIR | Stereo Camera | Single Camera |
| Type | Active | Active | Active | Passive | Active | Passive | Passive |
| Cost | High | Low | Med | Med | Med | High | Med |
| Range (m) | <250 | <10 | <50 | <12 | <50 | <10 | <100 |
| Precision | Low | Low range | V. High | V. High | V. High | Med | Low |
| Resolution | Low | Low | Precise | V. High | V.High | Med | Med |
| Reliability | High | Low | High | High | High | Med | Med |
| Power | High | Med-High | Med-High | Low | Med | Low | Low |
| Processing | Fast | Speed of sound limits | Fast | Med | Fast | Fast CPU needed | Fast CPU needed |
| Rain influences | No but reduces range | Yes | Yes | Yes | No but reduces range | Yes | Yes |
| Dust influences | No | No | Yes | Yes | No but reduces range | Yes | Yes |
| Fog influences | No | No | Yes | Reduces range | Reduces range | Yes | Yes |
| Sound influences | No | If High pitch | No | No | No | No | No |
| Light influences | No | No | No | Direct sun | Direct sun | Lens flare | Lens flare |
| Temp influences | No | Yes | No | Can reduce contrast | Can reduce contrast | No | No |
| Other influences |  | Echoes Wind | Snow | Snow |  | Wind | Wind |
| Classifies object | No | No | In single plane | Yes | Yes | Yes | Yes |
| Light required | No | No | No | No | No | Yes | Yes |
| Single point Reliability | No | No | - | - | - | - | Static objects only |
| Research | (Blanche et al., n.d.; J. Huang et al., 2001; Mohammed et al., 2020; Norouzian et al., 2019; Schneider & Wenger, 2003; Yamauchi, 2008) | (De Simone et al., 2018b; Jiménez et al., 2014; Kapoor et al., 2018; Kleeman & Kuc, 2008; Mohammed et al., 2020; Rosique et al., 2019; Shing et al., 2008; Sulaimon Alli et al., 2018) | (Byeon & Yoon, 2020; Goodin et al., 2019; Lebakula et al., 2021; Lu et al., 2020; Mohammed et al., 2020; Wallace et al., 2020; J. Wang et al., 2016; Yamauchi, 2006, 2008; Zhong et al., 2020) | (L. Matthies & Rankin, 2003; Ren et al., 2020; Sulaimon Alli et al., 2018) | (Dwork et al., 2006; L. Matthies & Rankin, 2003) | (M. K. Cheong et al., 2016; Gao et al., 2016; Hautì et al., 2006; Karuppuswamy, 2000; Lecun et al., n.d.; Lwowski et al., 2014; Manduchi et al., 2005; Mannar et al., 2018; Michels, 2005; Nguyen Viet & Marshall, n.d.; Noori et al., n.d.; Odeh & Faqeh, 2009; Schäfer et al., 2005; P. S. Sharma & Chitaliya, 2007; Simmons et al., n.d.; Sun et al., n.d.; van Hecke et al., 2018; S. Wang et al., 2021; Yamauchi, 2008; Z. Zhang, 2012) | (Chaudhary et al., 2019; Hautì et al., 2006; Hoffman et al., 1999; Hoffmann et al., 2004; Karuppuswamy, 2000; Lecun et al., n.d.; Lwowski et al., 2014; Manduchi et al., 2005; Mannar et al., 2018; Michels, 2005; Nguyen Viet & Marshall, n.d.; Sun et al., n.d.; van Hecke et al., 2018; S. Wang et al., 2021; J. Zhang et al., 2017; Z. Zhang, 2012) |

Detection of holes in the ground (rabbit warrens or natural depressions) has been briefly explored (Ghaffari et al., 2004; Kusuma Arbawa et al., 2021; L. Matthies & Rankin, 2003; J. Wang et al., 2016) by using thermal signatures (infra-red) which works well at night provided that ground cover is not too dense but has limited effectiveness on a sunny day (L. Matthies & Rankin, 2003). Matthies and Rankin propose modelling solar illumination for their approach to be usable in daylight conditions.  
  
Determining and adapting to ground conditions has primarily been limited to detecting traction loss on the driven wheels and compensating by pulsing torque in a similar manner to anti-lock braking. The methodology is well developed and is the approach taken by full-size vehicles.   
Determining ground conditions before the rover reaches them has had less research. Khan and Ahmed (Khan & Ahmed, 2021) used a CNN (convolutional neural network) to detect snow on road images and Kawai (Kawai et al., 2014) used a car-mounted webcam to distinguish road conditions at night via colour differences but a road is a known surface and rural topologies vary considerably. Wading sensors as utilised by Tran (Tran et al., 2015) only face downwards and can’t predict the depth of water ahead of a vehicle.  
  
Compensating for ground elevation and slope has been treated extensively in both research and general industry, with a gyroscope being the most-used sensor used to detect the current gradient the vehicle is travelling on. Predicting upcoming gradients has had less research. A stereo camera techniques such as Schäfer’s (Schäfer et al., 2005) holds some promise for holes or negative gradients but their technique is not as applicable to positive gradients.  
  
The standard post and wire fence used in NZ farming is difficult to detect as the diameter of the wire is less than the detection scan resolution of many sensors. An ultrasonic sensor requires an object of at least 4mm in width, for instance. In this regard a lidar sensor ought to be better but very small objects may be missed. A very high resolution camera is possibly the best solution.  
If the fence needs to be traversed (a common occurence on a large farm), determining a suitable place to cross is somewhat difficult, especially where long grasses may cover a tunnel and/or a gap in the bottom wire.‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬ ‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬‬  
Wind effects acting on objects can make object identification difficult. Object identification when facing into the sun or other lighting challenges are also likely to be issues in a real-world environment.   
  
“Yolo”, “ImageAI”, “OpenCV” and other available Python modules can be used for object-detection but often require a GPU to calculate the processing requirements within real-time requirements. Models using C or C++ perform considerably better although there is a balance between speed and accuracy. (Druzhkov & Kustikova, 2016; Ljubičić et al., 2021; Rajavarshini et al., 2021). This project examines data in Matlab and leaves implementation for future work.

Biological neural network emulations have been attempted emulating a locust’s collision avoidance neural network (Blanchard et al., 2000) but three Pentium II PCs were required so this approach is not examined further.

Camera-based solutions to recognise obstacles

Cameras are often used in industry to perform obstacle detection as they provide many advantages.   
  
The photographic process is the art of capturing the light both emitted and reflected from an environment onto a device (light sensitive film or a digital light sensor) and faithfully representing this on the capture device as an image. The light is captured for a period defined by the photographer (the “shutter speed” of the captured photo defined in fractions of a second) through a size-adjustable hole, called an “aperture”, described as a ratio of the focal length or F-Stop.

In a digital camera, captured light is stored as a charge on a photodetector sensor, integrated over the time period desired (speed value). An infra-red filter is placed in front of the sensors to eliminate all Infra-red light and either a red/green/blue (RGB) or cyan/magenta/yellow (CMY) patterned filter in front of the sensors allows for RGB colour values to be extracted from the image by subsequent processing. In current complimentary silicon oxide semiconductor (CMOS) sensors, charge amplifiers are built into the pixel arrays to reduce noise. The resulting analogue signal is then converted using an analogue to digital converter (ADC) in a matrix fashion (rows and columns). Refer to Figure 2.1  
The size of a pixel array (rows by columns) determines the resolution of an image – how much detail is available. The resolution of the ADC (number of bits) determines the colour resolution – how many different colours can be resolved. Storing high resolution images requires significant storage space so most images are compressed to reduce the image size. (Fossum, 1998) Various compression algorithms are used, with the most common being the Joint Photographic Expert group (JPEG or JPG) coder/decoder (codec) with a typical compression rate of 10:1 with little visually perceptible loss (JPEG, 1994). The output file format also stores image metadata and is normally either in EXIF (JEITA, 2019) or JFIF (from the same JPEG group as the JPG format) formats with EXIF, the most common.

A diagram of a person's vision

Description automatically generated

Figure 1‑6 Digital camera system.Image from (Fossum, 1998)

A video stream is a collection of images and the rate of images (frames) stored per second is a measure of the video quality (along with the already-mentioned image quality). A high resolution image captured at a high frame rate is of higher quality than that of lower resolutions and lower frame rates. Video processing uses different codecs to compress the images such as x264 (ITU, 2010) and x265 (ITU, 2013) and the resulting video data (along with coded audio data, subtitles and other metadata) is stored in a container format, the most common being Motion Picture Expert Group 4 (mp4) (ISO, 2020) or Matroska (mkv). (Matroska, 2015).   
  
A camera coefficient matrix is established in a manner similar to the equation below. where fx and fy are the camera focal lengths and cx and cy represent the optical centre of the camera in pixel coordinates. This matrix is used to apply correction for lens characteristics.

K=

Equation 1.1 Camera coefficient projection matrix (Odelga et al., 2017)

The lens distortion characteristics will need to be determined as per Equation 1.2 below, where ( x, y ) are the measured coordinates, ( , ) are the corrected coordinates and ( xc, yc ) are the centres of radial distortion, assuming a unity aspect ratio. L is the distortion factor. (Hartley & Zisserman, 2004)

Equation 1.2 Equations to correct for lens distortion (Hartley & Zisserman, 2004)

The function L(r) will need to be derived from a comparison with a linear mapping chart., or a taylor substitution approximation can be applied where the kn coefficients relate to the internal calibration of the camera such that

Equation 1.3 Deriving the distortion function. (Hartley & Zisserman, 2004)

Obstacle identification is generally based on edge detection – determining objects by recognising the boundaries of the object. "Canny" (extension of "Sobel") Edge Detection (Ganesan & Sajiv, 2018) and "Fuzzy" edge detection (Haq et al., 2015) (for images with a high noise floor) are the standard methods of edge detection.  
  
The Matched Filter extension to the Canny approach (Ofir et al., n.d.) is interesting as the algorithm is designed for soft (curved) edges (more likely to be present in a natural environment) but the curved edges evaluated were letters and numbers in a 2D image rather than a receding three-dimensional image plane. Run times for their optimised algorithm (using sampling) were 0.6 seconds using C++ on an I7 with 16Gb of Ram with an image of 129x129 pixels). For a 257x257 image, run time was 5 seconds which is too slow for real-time use on a rover.  
  
Utilising wavelet analysis is a very interesting approach, is almost perfect in resolution and would work with a receding plane BUT the authors state the process is not useful in noisy environments (Damlamian & Jaffard, 2019) and the processing requirements of a “Datacube MV200”, 68040 CPU and a “Sparcstation” workstation, as implemented, are too computationally (and economically) expensive for a low cost battery-powered rover.  
  
Utilising a muti-spectral camera system enables detection of soil and vegetation (Larry Matthies et al., 1995) but would involve power and computation usage beyond the rover’s capabilities unless filters could be dynamically applied to a camera.

#### Sensor fusion approaches

As a rover should operate in all weathers and conditions, multiple sensors are likely to be required to compensate for the deficiencies in each sensor type.  
  
Multiple sensor calibration has been investigated thoroughly at a basic level of integrating two sensors (Rodriguez F. et al., 2008; Zhou et al., 2018) but integration of more than two sensors appears to be lightly touched in research.  
  
Manduchi et al. (Manduchi et al., 2005) implemented a combination of a colour-stereo camera to categorise grass, bark, soil and rocks, holes, etc. along with analysis of a single-axis lidar to detect rocks partially hidden by grass. Manduchi found soil/dry grass categorisations was difficult with pure colour matching and they suggested additional techniques such as visual texture mapping or multispectral thermal analysis. (Castano et al., 2014; Gilmore et al., n.d.)

### Image stabilisation

As a video stream is a successive stream of photos, a video stream can be used to determine motion of objects around a vehicle by determining the location of an object (often called a “feature”) in a photo frame, and then comparing its location in subsequent frames. (If a feature is static, the same process can be used to determine the velocity and direction of the vehicle). For this approach to work, initial feature detection is required and as the vehicle passes this feature, new feature/s will need to be acquired and used for comparison. The vehicle’s own movement (including any chassis vibrations) will also need to be accounted for.   
  
What makes this approach more problematic is that, in rural New Zealand, the topology may not be smooth, and so our vehicle (and therefore it’s camera) will be susceptible to jostling while travelling, making feature detection difficult. At an excessive level of movement, the feature/s may not be present from frame to frame.   
  
One solution to this problem is to use optical image stabilisation (OIS) where an image stabilisation control system is placed within the camera lens (this being the ideal place as it acts as a force multiplier compared to the sensor location) and/or to the camera sensor. This technique is designed for countering the vibrations caused by hands shaking whilst holding a camera. If the system senses movement to the left (normally via a hall-effect sensor), it will move the lens or sensor to the right to compensate. This approach works well for small movements but limits on the mechanical range of the servometers (servos) used prevent this technique from compensating large movements and there may be time lags due to inertia of the detection and mechanical components. Another issue with this technique is that the cost to implement OIS in a camera system is high.   
  
An extension to this technique is to use a gimbal – an external system mounted to the camera system comprising of a gyroscope that is controlled by larger servos. This system copes with larger movements than an in-camera system but still suffers from mechanical range and inertia issues and requires a hysteresis system to prevent oscillations if a vehicle is moving fast with large displacements. This method may also prevent the camera system from looking ahead down a path if the vehicle is travelling on an incline or decline.  
  
A direct approach is to utilise a wide point of view lens such as a “fisheye” so feature may stay in the frame even with large movements however this introduces significant lens distortion which will need correction in software, plus a circular fish-eye lens will only use the centre area of the sensor, reducing image quality, due to the image cropping required.

A road with yellow paint on it

Description automatically generated

Figure 1‑7 Fisheye Lens capture example. Image from (BHPhotoVideo.com, n.d.)

The other approach is to use digital stabilisation, of which a few methods exist.  
  
The first method is to use the same feature-mapping solutions used to determine obstacles but to select a static feature that can be tracked from frame to frame. One problem with this approach is that, as the vehicle is moving, the change in perspective will lead to distortion as shown at (Android Authority, n.d.-b). A potentially greater problem is that the purpose of image stabilisation is to enable feature detection, yet feature detection is required to stabilise the image, so the selection of which features to track is critical to the success of this method.  
Feature tracking is computationally expensive and complex. Feature mapping has limitations on image size and the amount of displacement as increasing both increases processing requirements. Current research has focused on efficiency improvements such as the SIFT (Battiato et al., 2007; Chao et al., 2013) and SURF (Ljubičić et al., 2021; Shene et al., 2016) methods, along with other approaches such as affine-transform matrices (Mai et al., 2012; Mingkhwan & Khawsuk, 2017; Schwertfeger et al., 2011; Shen et al., 2009; Thillainayagi & Senthil Kumar, 2017) which compares separate video frames, particle filters (J. Zhu et al., 2016), linear and curve filters (L. Wang et al., 2012) and iFMI spectral registration (Schwertfeger et al., 2011). Hsu (Hsu et al., 2005) concentrated on hand-held camera shake using an inverse triangle technique while Morimoto (Morimoto & Chellappa, 1998) compared 4 DIS algorithms and found that simpler models performed better than more complex algorithms, due to them being less sensitive to tracking errors. Ljubičić et al. (Ljubičić et al., 2021) outlines freely-available software applications for applying digital image stabilisation. Once the direction and velocity of the camera movement has been determined matrix mathematical operations are used to apply this vector in the opposite direction to counter the effects of the movement.  
  
The second method is to apply sensor fusion where camera movement can be compensated by an external sensor such as a gyroscope and/or accelerometer. This approach is similar to the gimbal OIS method except that the calculated movement is compensated for by translating the image in the opposite direction and velocity of the movement using software. The same matrix mathematical translations as with feature tracking are then applied. The most common sensor utilised with this approach is using an Inertial Management Unit (IMU), a sensor combining a gyroscope and accelerometer together to give 6 degrees of freedom detection (6DOF). Adding a magnetometer gives 9DOF, adding an additional barometer/temperature gauge outputs 10DOF and adding a GPS sensor to that gives 11DOF.

For an Inertial management unit (IMU) to compensate for unwanted movement in video streams, a vector of the resulting movement needs to be created so that the pixels in each image frame can be rotated/translated by the amount of unwanted movement.  
  
The gyroscope on an IMU outputs data in angular velocity which is a measure of rotation measured in angles of movement per second and is expressed in revolutions, radians or degrees per second per each axis of the three dimensions, x, y and z. An accelerometer measures acceleration in the same three dimensions and outputs data in m/s2.   
  
For a vector to be created, the rotation measured by the gyroscope needs to be converted into angles of roll (how much the vehicle tilts from side to side or rotation around the x axis), pitch (how much the vehicle rises and falls or rotation around the y axis) and yaw (how much the vehicle moves horizontally to the left or right or rotation around the z axis). Note that this convention is not strictly defined, and one may place the x, y and z -axes in any direction that is convenient, providing the angled relationships between them remains fixed.

Diagram of a truck with the same body and the same body

Description automatically generated with medium confidence

Figure 1‑8 Diagram of roll, pitch and yaw angles. Image from (Fang et al., 2013)

The mathematical process to do this incorporates integration which introduces a cumulative error, the size of which depends on the number of samples. This error is known as gyroscope drift as, with a static measurement, the resulting output will incrementally diverge with each integration operation. The results of this can be seen in Section 4. Gyroscope also have bias and general noise issues, particularly at low frequencies.  
  
The general process of using an IMU is expressed in the following mathematical equations.  
At rest, gravity will be the only acceleration acting on the IMU, and assuming it is mounted so the z axis points straight down, the acceleration matrix will be  
where g=9.81m/s2. The acceleration in a tilted frame will be   
where ai refers to the acceleration values for each axis.   
Euler angles are generally used (in particular the 3-2-1 set) referred to as yaw, pitch and roll.  
Using a direction cosine matrix, the relationship between the tilted frame and level frame is:

Solving for pitch and roll, we get:

Using an accelerometer in this manner is subject to high levels of noise, as amongst other errors, any movement of the vehicle will corrupt the measured value of gravitational acceleration.  
  
Magnetometers can give an accurate measurement of the gravitational field but are influenced by other sources of magnetism, and in this case, the camera and front IMUs are mounted close to an electric motor.

To measure orientation using a gyroscope, an initial orientation must be known and then measurement values are integrated over time are computed. Integration of errors will lead to an incremental error components in the calculated value.

We can then multiply the pitch and roll angles to our video frame data using matrices to transform the moving frame data to a purely horizontal reference as described by Odelga. (Odelga et al., 2017)

This approach has been explored previously. Karpenko used the gyroscope on an iPhone to stabilise videos by iteratively calculating the differences between frames rather than directly using immediate orientation values (Karpenko et al., 2011). Jiang used an IMU to adjust both OIS (in strict x=0 and y=0 directions) and DIS stabilisation algorithms for the z-axis (Jiang et al., 2010) but did not provide real-world results.  
Stegagno et al used integrated IMU and Dense visual odometry pose estimation using a RGB-D camera (requiring indoor operation) and pan-scanned the drone to increase field of view for a haptic-tele-operational drone. They proposed using a stereo camera for outdoor operation. Their experiment constrained the drone to 3 degrees of freedom, where roll will be present in this project.  
Wiriyaprasat and Ruchanurucks used a full attitude and heading reference system (AHRS) unit (this has an onboard processor to provide attitude and heading rather than outputting raw gyroscope and accelerometer values as an IMU does) with Iterative Least Squared Error methods to modify a homography matrix to accommodate more rotational differences than a normal homography matrix. Calibration of the sensor to the camera was required as these were not installed in the same plane. A constant was required to change the pitch angle which they could not explain.  
Odelga’s team used both gyroscopes and accelerometers of the IMU on a drone and used the accelerometer values to compensate for the gyroscope drift, using a complementary filter. They also implemented fish-eye RGB-D lenses to get an improved field of view and compensated for the distortion introduced by this lens (Odelga et al., 2017). All of the approaches listed above only utilised single IMU units.  
  
The third method combines feature detection with IMU data to improve accuracy and speed of a feature detection system like Ryu and Auysakul (Auysakul et al., 2018; Ryu et al., 2010) who implemented an IMU to assist with a KLT tracker algorithm. Auysakul later used the IMU to drive servo motors as an OIS technique (Auysakul et al., 2019). The same issues with a feature system still apply with this method but accuracy and speed are increased. Chang et al (Chang et al., 2016) extended the use of an IMU by utilising a TLD (Tracking, Learning, Detection) multi-layer classification algorithm coupled with mechanical servos to compensate for the camera movement using OIS techniques. The main benefit of the TLD algorithm is the fuzzy logic controller algorithm dynamically updates the feature points. Utilising servos is only applicable if the motive movement and jostling are slow enough for the servos to compensate, and the servos have sufficient range of motion, both of which did not seem practical when implemented on a rover. As discussed earlier, feature detection is a computationally expensive process for the typically limited processing resources available on a rover.  
  
The common issue with all stabilisation systems is that a portion of the image will need to be cropped to act as a buffer for varying movement, the effects of which can be seen at (Android Authority, n.d.-a). If these effects are to be avoided, further cropping of the image is required, reducing quality.

Utilising multiple IMUs to compensate for errors in a single IMU has been investigated (Madgwick et al., 2013) but Madgwick only utilised accelerometers in the array.  
  
The neural network or artificial neural network (ANN) or multilayer perceptron (MLP) has come back into fashion in recent years due to its use in many machine learning applications. Originally designed to mimic the biological brain, these supervised machine learning models can predict an output from given inputs and are optimised for classification (discrete outputs – typically a category of some sort) and/or regression (usually continuous outputs) tasks.   
  
A neural network is a collection of interconnected neurons that incrementally learn from data to capture both linear and non-linear trends to provide predictions for new situations containing even noisy and partial information.  
  
The basic unit of a neural network is the neuron. A neuron applies a weighted average function across input data and then applies a nonlinear “input/output” function as shown in Figure 2.2

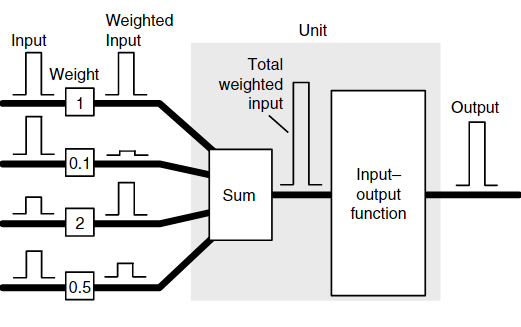


Figure 1‑9 Neuron construction (the unit part of the diagram). Image from (Samarasinghe, 2006)

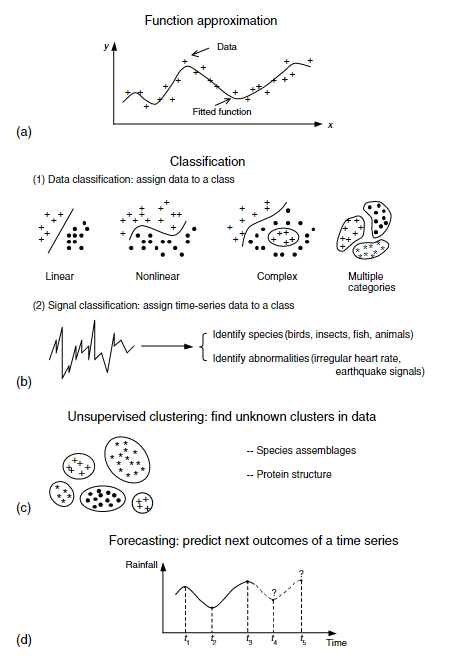
One of the inputs is usually given a value of 1 and called a bias input. This input is used to account for output effects that are not accounted for by the other inputs.  
  
Training data is used to train a network and must consist of input values and associated correct output values. Training involves iteratively randomly changing the value of the weights until the system learns to perform the task properly (the system’s output matches the training data output).  
The differences in output between the training data and the neural network’s outputs during training (or error) is determined by either simple subtraction for simple networks or a least-squared-error approach for multilayer networks. As the least-squared-error function is parabolic, the network calculates the error gradient in a downward direction along the curve to determine an optimal solution. A process called backpropagation is used to determine the error contribution of each weight and therefore how much each weight should change in the next iteration of the learning process.  
   
The overall function of a neural network is determined by the network structure, the connection strengths between neurons (called a weight) and what activation functions are used at each neuron.  
  
Some examples of the type of functions and their use is show in Figure 2.3   


Figure 1‑10 Example functionality of neural networks for scientific data modelling: (a) fitting models to data or regression, (b) complex classification tasks, (c) discovering clusters in data, and (d) time-series forecasting. Image from (Samarasinghe, 2006)

Examples of the types of network topologies and their indicative uses are shown in Figure 2.4

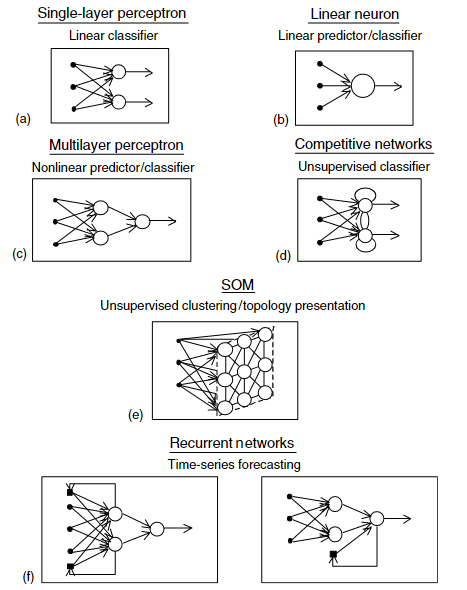


Figure 1‑11 Some neural network topologies: (a) single-layer perceptron, (b) linear neuron, (c) multilayer perceptron, (d) competitive networks, (e) self-organising feature maps and (f) recurrent networks. Image from (Samarasinghe, 2006)

Multilayer Neural Networks have an input layer, an output layer and, commonly, one or more “hidden” layers between the input and output layers. These tend to be configured as supervised learning systems where the weights of the neurons are adjusted until the difference between the correct output and the neural network output reach an acceptable level, as determined by utilising a least square error method along with determining the negative gradient of the error function.

Other types of neural network such as convolutional neural networks (CNN) exist which are optimised to create feature maps of data which can be used to determine shape and texture of data.  
A CNN neural network identifies features very well and is ideal for the classification of obstacles. For image stabilisation, a CNN network implementation was not deemed to be necessary and a multilayer perceptron approach will be selected.

The types of neuron input/output functions are varied and depend on the purpose of that neuron in the neural network.   
Common functions are a threshold function where the output is mapped to either 0 or 1 for use in classifying data.  
Competitive learning models various neurons become active and the ones that receives the largest input values “win” over the others and are weighted more. Over time the model can be said to become more sensitive to types of input data that they respond best to, and over time, various neurons become specialists at particular input types. This type of model is designed for competitive situations and/or self-organising feature maps and is not applicable to this project.  
  
Supervised learning uses a sample of the input/output data as training data and uses the following three basic techniques:  
1) forced learning, which is somewhat similar to the competitive learning model  
2) Reinforcement learning, where feedback is applied to improve the responses over time.  
3) Supervised learning, where the actual error differences between input and output are used to change weight values, based on an error gradient.   
  
An epoch is defined as one pass of all training data input patterns into the network. Many epochs may be (usually are) needed across the input data until the weight optimisation process is complete.  
  
Accuracy of a neural network is defined as the percentage of patterns correctly classified for each classification over the entire dataset. Once a suitable level of accuracy has been achieved the neural network is ready for live data.  
As can be seen, neural networks are not magical and will not solve all problems. They require the practitioner to understand the datasets involved to design and configure a neural network system that will correctly classify/regress incoming data.

## Research Objective

The primary objective of this project is to determine whether multiple Inertial Measurement Units in conjunction with a neural network can improve image stabilisation of a camera on an RC vehicle, compared with a single inertial management unit.  
A secondary objective is to determine the least number of Inertial Measurement Units required to provide a significant measurable improvement.  
Another secondary objective is to evaluate if multiple IMUs give more information about the state of the vehicle than an single IMU and if this information is obtainable, can it be useful to determine applied vehicle acceleration.

## Thesis Outline

Chapter 1 (this chapter) provided an overview of the motivation, objective and results of the project. Chapter 2 discusses prior research that is relevant to this project, which involves the concept of a data mule, obstacle avoidance approaches, image stabilisation and neural networks. Chapter 3 describes the methods used in the project, including the approach taken and the resources and tools required. Chapter 4 presents the results of the project and these are discussed and analysed in Chapter 5. Chapter 6 provides conclusions and suggests paths for further research. Chapter 7 provides the code used and Chapter 8 outlines the references.

# Literature Review

This chapter reviews current literature on the application of Inertial Measurement Units (IMUs to image stabilisation problems. It outlines approaches that have been used and their benefits and drawbacks. The chapter concludes by identifying research gaps and identifying the research question(s) for this project.

As mentioned in the introduction, an IMU can be used to provide accurate positioning however using acceleration and magnetic data can introduce noise and gyroscope data has inherent drift, caused by integrating the rotational data into angles of roll, pitch and yaw. Various methods have been proposed to counter this drift.   
  
One mitigating factor is to obtain a gyroscope with a low zero-rate offset value so this integration error is minimised. Gyroscope selection is critical. (La Rosa et al., n.d.)  
  
To counter gyroscope drift and bias errors, accelerometer arrays have been proposed (Madgwick et al., 2013) but these lack real world testing and implementation.  
  
Compensating for gyroscope errors with accelerometer (with a gravity vector) and magnetometer (with magnetic north) readings has been explored as the latter do not depend on prior state knowledge, as a gyroscope does.   
The most common algorithms for performing this fusion are complementary filters (Odelga et al., 2017; Yoo et al., 2011), Kalman filters and optimisation filters (Yean et al., 2018).

Complementary filters are computationally efficient and easy to implement but are subject to noisy and biased data and are susceptible to gyroscopic drift around the z axis and are thus not reliable or robust enough for regular use over time. (Madgwick, 2010) Kalman filters provide very accurate orientation (Higgins, 1975; Marins et al., 2001; Sabatini, 2006) in the presence of large noise values such as persistent acceleration however are computationally expensive and complex (Yuan et al., 2019). Optimisation filters estimate a vector representing the sensor output at the current orientation and attempt to minimise the difference between predicted and measured results. [12]. Optimisation filters have acceptable accuracy with lower computational expense than Kalman filters but can suffer from unpredictable convergence (Fan et al., 2017; Mahony et al., 2005; Yean et al., 2018).   
  
A software approach proposed by Odelga et al (Odelga et al., 2017) feeds both gyroscope and accelerometer data from a drone into a complementary filter, with a constant gain value, determined empirically to reduce the drift error without ignoring vehicle acceleration. The use of a complementary filter rather than the more widely implemented Kalman filter reduces processing requirements. Using this approach with a very wide-angle (“fish-eye”) lens permitted a wide viewpoint, allowing for compensation of very large movement displacements.   
The angles obtained were compensated for by a complementary filter with a gain factor constant carefully selected so that the vehicle’s own motive acceleration does not introduce errors.  
Odelga found that the IMU solution worked well and utilising “fish-eye” cameras with large fields of view reduced the issue of a feature disappearing between subsequent images, but introduced barrel distortion which needed to be compensated for.   
  
In 2011 Madgwick et al introduced a gradient-descent algorithm commonly called Madgwick’s algorithm (Madgwick et al., 2011) which is more computationally efficient than Kalman filters and is currently widely used in industry (Fan et al., 2017; Yean et al., 2018) but requires two sequential minimisation steps (first on the magnetometer and then on the accelerometer) which can lead to slow convergence, the calculations of roll and pitch are not decoupled from each other which can lead to unpredictable orientation errors and a single adjustable parameter made it difficult to combine accelerometer and gyroscope values (Fan et al., 2017).  
  
In 2020 Madgwick et al extended a complementary filter in quaternion form (Euston et al., 2008) based on Mahoney’s work (Mahony et al., 2008) to increase robustness against noise while maintaining low computation cost and predictable convergence efficiency (Madgwick et al., 2020) and made this algorithm open source. (X-IO, 2008). It decouples roll and pitch data and varies the gain factor from a high value at initialisation to a lower running value to improve initialisation time.  
There are two variants of this algorithm, one in which magnetometer information is combined (IECF) and the other with only accelerometer and gyroscope values included (IECF6). Fan found that when magnetic disturbances were present, the IECF6 algorithm performed better. Fan also outlined that including magnetometer data was important to provide a single point of reference when using multiple IMU units. (Fan et al., 2017) Yean’s approach of using a complementary filter to counter gyroscope drift, combined with a Kalman filter / gradient descent algorithm worked well for slow and controlled ranges of motion, and so, is not suited for a bouncing vehicle.  
  
Madgwicks IECF6 algorithm will be used as the control factor in this project.   
  
Multiple IMU solutions have been proposed before (see above) but none have suggested using a neural network to dynamically compensate for magnetometer and other errors across multiple IMUs. The concept of a neural network has been covered in the introduction.  
  
Using a trained back-propagating neural network with multiple IMUs should effectively compensate for drift and other errors present in a single IMU implementation and that is the model implemented in this project. Due to the computation requirements of a neural network, it makes most sense to apply this directly to sensor readings, rather than complementing Madgwicks algorithm, as the neural network should be able to determine the relationships.

# Method

In this chapter, the project methodology is outlined. The theory behind the system design is presented first with the implementation details following.   
  
3.1 System Design

The overall method employed is to capture simultaneous video and imu data at various states of motion and then analyse this data in Matlab to ascertain if using a neural network with multiple imus offer any improvement in video stability processing compared to a single imu using the Madgwick IECF6 algorithm.

A base control system utilising the Madgwick IECF6 algorithm is fed live IMU data to ascertain a control for the experiment. The gyroscope is set to a range of 0dps-250rps and the accelerometer is set to a range of 0g to 2g. The accelerometer values are normalised to the gyroscope values by multiplying by 100 (radians per second) as it is expected that the gyroscope values will not exceed this rotation rate.  
Different neural network topologies will be developed and trained on a subset of this same data and then fed the full dataset to determine which, if any, neural network topology offers any significant improvement over the Madgwick algorithm process.  
  
The matrix translation step of adjusting the video with the resulting roll and pitch angles is a known process and, as such, will be ignored in this project.

3.2 Method Employed  
  
The imu’s gyroscopes and accelerometers are first calibrated and then normalisation is applied to the accelerometer values (For both ease of verification and calculation, it was decided that multiplying the accelerometer values by 100 would scale them close to the expected gyroscope values of +/- 90 degrees, individual python scripts for IMU data capture and video capture are run simultaneously and the resulting datasets are manually synchronised. The contents of these scripts can be found in Appendix A.

The resulting data is fed into Matlab and a Madgwick AHRS function is used to determine the resulting roll, pitch and yaw values.  
  
The Madgwick function code is first run on video and Camera IMU data from a completely still rover to calibrate the sensors.  
Both the Madgwick function and the matrix translation are then subsequently run again on a single Camera IMU with the following movements to create a baseline performance level:

* Roll only
* Pitch only
* Yaw only
* Gentle combinations of all three movements.
* Fast combinations of all three movements
* Fast and large combinations of all three movements.

After the baseline performance level is obtained, a training subset of all IMU data is fed into a neural network and the network trained.  
Once trained, all remaining IMU data is fed into the neural network to determine if the neural network has improved performance.

## Equipment utilised

The data capture aspect of this project is implemented on a Raspberry Pi4b with 4Gb of RAM (Raspberry, n.d.), using Raspbian version 11 (Bullseye) operating system, running on a generic 16Gb MicroSD card, using the ext4 filesystem (mounted with no atime).  
The Pi is configured with ssh and I2C options enabled and synchronised to a reliable time source for accurate logging.  
Python 3.9.2 is used for data capture from the Sparkfun IMU-20948 IMU sensors (Sparkfun, n.d.) and Matlab 2023a is implemented on an HP Z230 workstation (quad-core Xeon E3-1270v3@3.50GHz CPU with 32Gb of DDR3 RAM and 1Tb Samsung 860QV0 SSD) running Windows 10 Pro 22H2 for data analyis.  
A Tamiya “Bruiser” 1/10 scale radio-controlled vehicle is used as the field-testing vehicle as the footprint of the model is smaller than the 1/5 or other scale model that would most likely be implemented and should more readily react to changes in topology than a larger vehicle (Tamiya, 2012). The unit is to be assembled as it comes as an unassembled kitset. A generic 2-channel RC radio system is used to drive the vehicle, but due to the limitation of two channels, this requires manual pre-selection of the gear when operating.  
A signboard (aluminium with a plastic layer on each side) board is mounted above the vehicle to ensure rigidity and that all IMUs are mounted in the same horizontal plane, simplifying calculations.  
The aluminium layer in the signboard acts as a paramagnet and so, with an electric motor mounted below the main sensors, the algorithm employed will only utilise gyroscopic and acceleration values from the imu.  
  
Additional python modules to be installed are sparkfun\_qwiic, sparkfun-qwiic-tca9548a (to drive the multiplexer), board (to simplify addressing), adafruit-circuitpython-icm20x (to communicate with the ICM-20948 IMUs). Change the dtparam=i2c\_arm=on line in /boot/config.txt to read *dtparam=i2c\_arm=on,arm\_baudrate=1000000* and reboot as this will enable a 1Mbps baud rate, giving an effective sampling rate of the IMU units of up to 500kb/s.  
Install the opencv-python package (to drive the NoIR camera) from source via pip3 install git+https://github.com/opencv/opencv-python. (This avoids a known wheel dependency issue).  
Finally scipy (apt install python3-scipiy) and thenumpy and matplotlib pip libraries should be installed to aid in calibration.  
  
A Universal Robots UR5 robotic arm (Robots, n.d.) was used for both calibration and positioning to ensure that all methods employed could be verifiied against known angles.  
Programs were developed to move the robot to and from known angles to verify imu positioning.

## Initial baseline configuration

An initial baseline is developed to provide a control. The data for all IMUs is captured even though the initial baseline configuration utilises only the camera IMU data to mitigate against artifacts brought in by measuring the imus differently when the Neural Network is applied.  
  
The hardware is to be assembled and tested and the required python libraries installed.  
  
The UR5 robot arm needs to be calibrated first. This was undertaken with a 1.5 meter long spirit level.

  
Figure 3‑1 UR5 Robotic Arm Base position showing mounted baseboard

Initial IMU calibration is to be undertaken to determine offset values to be applied to the measurements. (See Appendix Section 7.X for the code used to perform calibration).  
Yaw movement data is not gathered as the IMUs would realistically require magnetometer data to derive this information and the aluminium baseboard (and steel construction of the vehicle chassis) would likely introduce too much variability to the measurements for a magnetometer to be useful. In production, fusing this data with a GPS unit would also allow location data to be obtained.  
  
A predefined path is set on the robot arm and the IMUs are polled during the arm movement. Alignment of the IMU and Robot arm data was done manually – in production, this alignment would not be necessary once initial IMU calibration was complete. The start of alignment was examined in Excel and then a Python script effectively reduced the Robot data entries down to the same number of entries as the IMU data, based on the offset alignment and the sample rate. The code for this is in Appendix 7.  
  
The robot arm code is run to obtain IMU data from a completely still and level rover first to achieve a baseline.  
The robot arm is then moved by the following variations. There is a 1 second delay between each angle movement unless otherwise mentioned.   
The results are analysed to ensure that the basic algorithm performs well in all states, and/or amendments to the algorithm are made to create a satisfactory baseline.  
  
The movements for each test are defined in Table 3.1.

Table 3.1 Angles of movement per motion test

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Motion | Angle 1 (Roll : Pitch) | Angle 2 (Roll : Pitch) | Angle 3 (Roll : Pitch) | Angle 4 (Roll : Pitch) | Angle 5 (Roll : Pitch) | Angle 6 (Roll : Pitch) | Angle 7 (Roll : Pitch) | Angle 8 (Roll : Pitch) |
| Rolling | 0 : 0 | -45 : 0 | -60 : 0 | Loop  x 5 | LoopA 60 : 0 | Loop B -60 : 0 |  |  |
| Pitch | 0 : 0 | 0 : 30 | 0 : 45 | 0 : 60 | 0 : -30 | 0 : -45 | 0 : -60 |  |
| Mixed | 0 : 0 | 15 : -30 | 30 : -45 | 45 : -60 | 60:-105 | 45 : 45 | 30 : 0 | 45 : 30 |
| Live | 0 : 0 | 60 : -30 | 30 : -45 | -60 : 30 | 60 : -30 | Loop x 5 | 30: -30 | -15: 30 |

The captured IMU data during these movements is entered into Matlab and processed using the code described in Section 7.4.  
  
  
To load the results into Matlab, the following process was used:  
  
Import the imudata csv file into a blank Excel file, ensuring that the date column (3) is set as text.  
Rename this Sheet to “All"  
Count the number of rows and columns for next step.  
Create new sheets with the following filters (example shown is for Camera IMU data).  
=FILTER(All!<completedatarange>,"CM"=All!<alldatainColumn1>)  
Create extra sheets for all 5 IMUs based on the formula above.  
Select the CM sheet and save the file as a “<name>-CM” csv file. We now have Camera IMU data.  
  
Load associated robot data csv file into another Excel file, ensuring column 2 is text.   
Remove any python artifacts in the file, if present.  
Compare the two files to find when both the robot and the imu data first register movement.  
Take note of the line entries in both files when this occurs. Ie. 39268(robot) and 339 (imu).  
Difference of these two (in this case) is 39929 which is our offset bias.  
  
Modify reduceRobotData.py to enter this offset bias value, the IMU CM filename and the associated Robot txt file and then run the code. This will generate robot data synchronised to the imu data.  
  
Once data is synchronised it can be imported into Matlab.  
Use the appropriate matlab command files in the github repository to import the data and run the Madgwick, Kalman and Neural Network operations across the data.  
  
The Madgwick filter is run first on the IMU results – the calculation is run 10 times and an average taken from this (Matlab timing accuracy is not defined for measurements below 0.1 seconds)  
   
The same dataset is fed into the Matab “imufilter” error-state Kalman filter and a regression type Neural Network.  
Additional runs on the Neural network were based on the front three IMUs (Camera, Front-Left and Front-Right) and all five IMU readings to determine if multiple IMUs would create more accurate output.  
  
  
Although all 5 IMUs were measured during operation, only the single Camera IMU is considered in the initial baseline configuration. This is because default settings of the Madgwick, Kalman and Neural Network filters expect a single IMU input. Once the working baseline model has been developed, the steps of 3.3.1 are repeated with the Kalman and neural network models (using single camera, the front three IMUs and then all 5 IMUs in operation) and results gathered.  
  
In Chapter 4, the results from these experiments will be detailed and discussed, with analysis of these in Chapter 5 and conclusions reached in Chapter 6.

# Results

## Initial data capture and calibration

A sample of the raw IMU data taken from the stationary vehicle is shown below in Figure 4.1. All IMU data is captured but only the Camera IMU data is used. The large value of Z is a measure of gravitational acceleration. This was measuring an average of 10.22617 m/s2 instead of the expected 9.80665m/s2. The maximum variation between sea level to the top of Mt Everest is approximately 0.02m/s2 so the discrepancy does not relate to altitude. (These measurements are taken at approximately 19m above sea level). Varying the mounting positions of the sensors slightly by tightening the mounting nuts changed these values by significant amounts, demonstrating that sensor positioning is of critical importance for accurate results. Once the sensors were mounted firmly on the chassis board, results showed that some sensors were mounted incorrectly in terms of consistent X and Y directions. The incorrect sensors were remounted, tightened down and readings taken again. This data can be referenced in the Appendix, chapter 7.  
To reduce the impact of outlying values, the 95th percentile values of the data was derived and used to calculate the average value of the data.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Accel\_X average ms/s2 | Accel\_Y average ms/s2 | Accel\_Z average m/s2 | Gyro\_X average degree/sec | Gyro\_Y average degree/sec | Gyro\_Z average degree/sec |
| -0.19154 | 0.11971 | 10.24718 | 0.027712 | 0.006262 | -0.01092496 |
| -0.1652 | 0.043096 | 10.27831 | 0.031043 | 0.004663 | -0.01652067 |
| -0.17957 | 0.050278 | 10.20888 | 0.033441 | 0.001732 | -0.0085268 |

Table 4.1 First three lines of data from the Camera IMU

A Jaycar KJ8916 robotic arm (Jaycar Ltd, 2023) was initially implemented to validate these measurements but this proved to be incapable of the task as the weight limit was 100g and the board, without battery, weighed 486g. On top of this, the KJ8916 robotic arm had significant play and movement was in approximately 1 degree increments on the main stepper motor.  
A set of setsquares (permitting fixed angles of 0,30,45,60 and 90 degrees) was initially used to calibrate the individual IMU sensors to apply appropriate offset and bias values (in the case of the accelerometer sensor).  
The gyroscope calibration is easiest to determine so is dealt with first.  
At rest, all gyroscope readings should be zero so averaging the deviations from this should suffice for a bias offset value in each axis direction. Table 4.2 lists gyroscope offset values for the Camera IMU.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Axis | Flat, Facing Up | Flat, Facing Down | 90deg, tilting left | 90deg, tilting right | Tilting Up | Tilting Down | Average Offset |
| Gyro\_X | 0.029521 | 0.029307 | 0.028777 | -0.02387 | 0.028599 | -0.02385 | 0.029078 |
| Gyro\_Y | 0.004314 | 0.004279 | 0.018543 | 0.018462 | 0.003848 | 0.018154 | 0.004103 |
| Gyro\_Z | -0.01118137 | -0.0112 | -8.4E-05 | 0.000296 | -0.01144 | 0.000378 | 0.00743 |

Table 4.2 Initial Camera IMU Gyroscope Offsets

Table 4.3 lists the Accelerometer offsets for the Camera IMU. These were obtained from the axes shown in the table and the Matlab polyfit function (Matlab, 2023) was used to determine the first order equation parameters of slope and offset. X values used were -1, 0 and 1.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Axis | Flat, Facing Down (gravity = -1) | 90deg, tilting left  (gravity = 0) | Flat, Facing Up (gravity=1) | Slope | Offset |
| Accel\_X | 0.02984 | 9.720203 | -0.20886 | 0.0013 | 0.0315 |
| Accel\_Y | -0.10395 | -0.59628 | 0.032943 | -2.338e-4 | 0.0325 |
| Accel\_Z | -9.4977 | 0.368226 | 10.22617 | -1.0244e-4 | 0.0325 |

Table 4.3 Accelerometer Slope and Offset Table

The offset and scaling values from Tables 4.2 and 4.3 are applied to each measurement to reduce calibration errors.   
Variation in the output matters as it may mask any differences in technique. Note that there is some considerable variation in the output for a completely stationary vehicle, indicating high noise floor of the sensors. The Madgwick, Kalman and Neural Network processes are meant to reduce these errors, providing they are gaussian in nature.  
  
The set square method is adequate for static calibration but it is desired that dynamic angles are also known when comparing the different methods so a stronger robotic arm was sought.  
  
A Universal Robots UR5 arm was available at Canterbury University and this was used to obtain new calibration and dynamic results.  
The robot joint angles themselves are not calibrated and show slight errors when manually compared to a 1.5m long spirit level. It is believed that, in this instance, this is mainly due to the visibly obvious bow in the wooden table used to mount the robot. These were initially compensated for but meant that the robot sensor data showed slight variations away from true positions. Using tool center point (TCP)sensors on the tool section of the arm showed true values of the pose compared to the spirit level however so the TCP sensors are to be used in measurements.   
  
When operating the robot it was seen that there is some tolerance and play in moving repeatedly between the same defined angles. In section 5.1 of the user manual, worst case joint position accuracy is given as 1.15 degrees with a detection time of 100ms. The tool center point (TCP) sensors have a worst-case accuracy error of 20mm in positioning and 1.15 degrees in orientation. These are worst-case values and it is expected that the robot should operate well within these limits.

With the robotic arm in the neutral position as shown in Figure 3.1, a sample of static results from the robot arm sensors is shown in Table 4.4.

Table 4.4 Sample of Euler angle results from the tool arm sensors (TCP or Tool Centre Point) when at rest on the Robot arm.

|  |  |  |
| --- | --- | --- |
| Euler\_Z | Euler\_Y | Euler\_X |
| |  | | --- | | 0.278238171 | | |  |  | | --- | --- | | 0.52853157 |  | | -90.0214431 |

Table 4.5 Joint angles of Robot at rest

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Angle | Base | Shoulder | Elbow | Wrist 1 (Roll) | Wrist 2 (Pitch) | Wrist 3 |
| Radians | [-0.0002992788897913101 | -1.570928399 | -2.3667E-05 | 8.39233E-05 | 1.5705477 | -7.230440248662262e-05] |
| Degrees | -0.017147417 | -90.00756717 | -0.00135602 | 0.004808453 | 89.98575473 | -0.004142737 |

Data reading rates for a single IMU is 8.333 readings per second (for all IMUs this is an average of 41.68 readings per second). The robot arm is sampled at approximately 4450 times per second. To ensure that the readings are approximately synchronised, the robot arm samples could be sub-sampled at 534.22 times per second, or, in this case, for every single IMU reading, take the 534rd reading of the robot arm results. This is not strictly accurate since the IMU capture may not start on an exact second boundary, and we are not using the actual floating point value, but, for this exercise, it is sufficient, as all angular calculation methods will use the same data set produced from this approximation.

The single camera data from the stationary vehicle producd 996 results within the 120 seconds of operation time.

The various orientation determination methods were applied with the following results.

## Baseline on a stationary vehicle: Madgwick filter

Applying the Matlab Madgwick function from Madgwick’s website (Madgwick, 2009) (code dated 28/08/2011) produced the following results on a stationary vehicle, demonstrated in Table 4.6. Settings for the Madgwick filter were left at defaults. These defaults were a sample period of 1/996, and a Beta gain value of 0.1. The time taken to process 996 sensor readings was 0.0426869 seconds using the tic/toc method in Matlab. As the code runs faster than the recommended minimum 1/10 second code runtime recommended for the tic/toc approach, the code was looped 10 times and the tic/toc result is an average. The results of the Madgwick filter are shown in Table 4.6 (TBC).

Table . Madgwick filter results from a stationary vehicle.

|  |  |  |
| --- | --- | --- |
| Angle X (Roll) | Angle Y (Pitch) | Angle Z (Yaw) |
| -0.2286 | 0.0278 | Varied from -0.0194 to 0.0217 |

A graph of the calculated data is shown in Figure 4.2.

A graph on a white background

Description automatically generated

Figure 4‑1 Madgwick filter results from a stationary vehicle (Brown=Roll,Yellow=Pitch,Blue=Yaw)  
  
The Yaw value shown in Figure 4.2 has a descending value over time due to the double-integration involved in producing yaw values from gyroscope information and clearly show that calculating yaw without magnetometer data is fraught with errors. The roll and pitch values vary slightly but values are within the noise floor of the sensor data.

## Option A on a stationary vehicle: Kalman filter

The default Matlab imufilter filter was used to represent an error-state Kalman filter with default properties.  
  
FUSE=imufilter(SampleRate=8,AccelerometerNoise=0.16,GyroscopeNoise=0.03,OrientationFormat='quaternion')start=tic;

q=FUSE(singleimudata(:,7:9),singleimudata(:,4:6));

EulerAngleOutput=quat2eul(q,'XYZ')

elapsed\_time=toc(start)

Running the Kalman filter above on the 996 sensor readings took 0.7581 seconds and produced an array of Euler angles after the conversion. Figure 4.3 shows the results and indicates that the Kalman filter can not handle yaw values (blue line) without magnetometer input. As discussed above, yaw values are not handled well by the filter for a stationary vehicle as the mathematical errors accumulate due to the double integration required to obtain the yaw value. Figure 4.4 shows a magnified view of the area around the x axis showing that the Matlab Kalman filter will produce accurate results to within 0.03208 degrees for roll values and within 0.0257 of a degree for pitch values. The computing time is considerably longer than the Madgwick filter (0.7581 vs 0.0426869 seconds).

A graph of a number of people

Description automatically generated with medium confidence

Figure 4‑2 Kalman Filter results from a stationary vehicle

A graph showing a number of results

Description automatically generated

Figure 4‑3 Magnified view of Kalman filter results from a stationary vehicle.

## Option B on a stationary vehicle: Neural Network

Using nnstart, and selecting a regression model on data from the stationary vehicle, the following data was produced.  
  
A screenshot of a computer

Description automatically generated

Figure 4‑4 NN Training data from a stationary vehicle

A graph of a number of data

Description automatically generated with medium confidence

Figure 4‑5 Validation performance data from a stationary vehicle

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Description automatically generated with medium confidence

Figure 4‑6 Regression performance data from a stationary vehicle

## Baseline on a rolling vehicle: Madgwick

The robot arm is to be rotated according to the appropriate angles in Table 3.1. The Robot arm data is synchronised with the imu data via manual alignment. The single camera imu data produced 1001 readings in the 120 second period.

The Madgwick filter was run on this data with standard settings of a Sample Period of 1/1001 and a default Beta gain value of .1 and took 0.0416698 seconds to run.  
The results were clearly incorrect as can be shown on Figure 4.8 below. Increasing the Beta gain uses the accelerometer values to compensate for the gyroscope values and results from various Beta values are shown in Figures 4.9 through to 4.11.

A graph of a graph

Description automatically generated with medium confidence

Figure 4‑7 Madgwick results from a stationary vehicle with a default gain of 0.1

A graph of a graph

Description automatically generated  
Figure 4‑8 Madgwick Filter on a rolling vehicle with a gain of 1

Using a gain of 10, the Madgwick filter took 0.0439530 seconds but produced better results as can be seen in Figure 4.10.  
A graph of a graph

Description automatically generated with medium confidence

Figure 4‑9 Madgwick filter on a rolling vehicle with a gain of 10

By repeated experimentation, a gain of 15 was the lowest gain required to produce the acceptable results show in in Figure 4.11. This operation took 0.0419838 seconds. The results from Figure 4.11 show a maximum measured value of 57 degrees instead of the expected +/- 60 degrees and the 45 degree setting was calculated as 42.9 degrees. If the 1.15 degree tool angle discrepancy plus the imu’s own 1.5% inaccuracy values are combined then this error is within the operating conditions of the sensors.

A graph of a graph

Description automatically generated

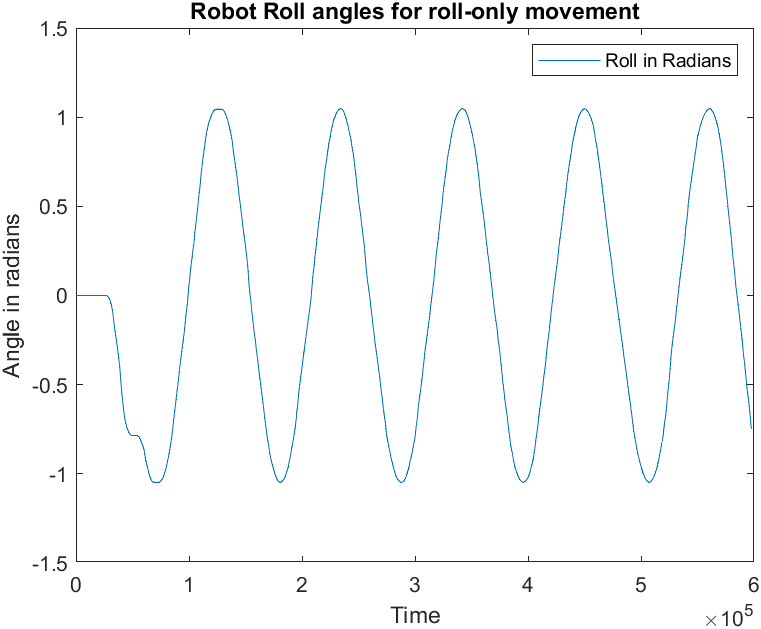
Figure 4‑10 Madgwick filter on a rolling vehicle with a gain of 15  
  
For comparison, Figure 4.11 shows the equivalent robot arm movement.  


Figure 4‑11 Rob ot arm movement details for roll-only experiment.

## Option A on a rolling vehicle: Kalman Filter

A Kalman filter was implemented using the standard Matlab imufiter function using the following parameters:

FUSE=imufilter(ReferenceFrame='NED',SampleRate=8.33,AccelerometerNoise=0.6,GyroscopeNoise=0.3,GyroscopeDriftNoise=3.04622e-2,LinearAccelerationNoise=0.0096236,LinearAccelerationDecayFactor=0.1,OrientationFormat='quaternion');   
start=tic;

q=FUSE(accel\_data,gyro\_data);

EulerAngleOutput=quat2eul(q,'ZYX')

elapsed\_time=toc(start)

The filter took 0.3195 seconds and produced the output shown in Figure 4.12. Smoothing of this data should be applied to these results but they track the movement of the vehicle adequately (Varying the Kalman filter settings did not show any significant difference in the output results). The average calculated value for the 60 degree angles is 59 degrees which is well within specifications of the sensors and tracks better than the 57 degree reading of the Madgwick result. The 45 degree angle was measured as 42.4 degrees which is (just) within specifications and tracks similar to the 42.9 degree reading of the Madgwick result.

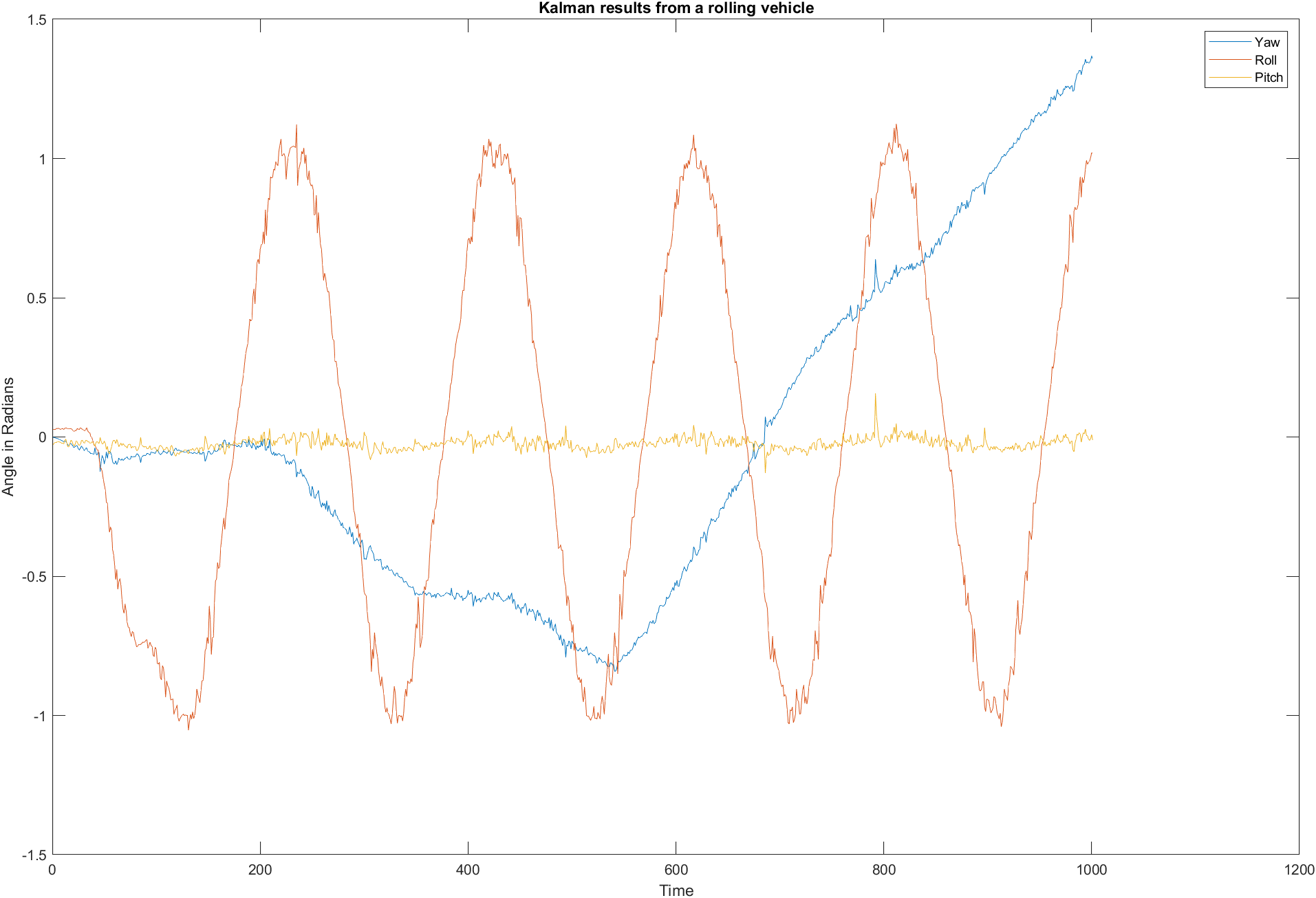


Figure 4‑12 Kalman filter results from a rolling vehicle

## Option B on a rolling vehicle: Neural Network

## Baseline on a pitching vehicle: Madgwick

For comparison, the robot arm movements for the pitching-only vehicle experiment is shown below in Figure <TBC>

A graph of a robot pitch

Description automatically generated

## Option A on a pitching vehicle: Kalman Filter

## Option B on a pitching vehicle: Neural Network

## Baseline on a rolling and pitching vehicle: Madgwick

The robot arm is to be rotated according to the appropriate angles in Table 3.1. The Robot arm data is synchronised with the imu data via manual alignment. The single camera imu data produced 995 readings in the 119 second period.

The Madgwick filter was run on this data with standard settings of a Sample Period of 1/995 and a default Beta gain value of .1 and took 0.0457350 seconds to run. Figure 4.12 shows these results.

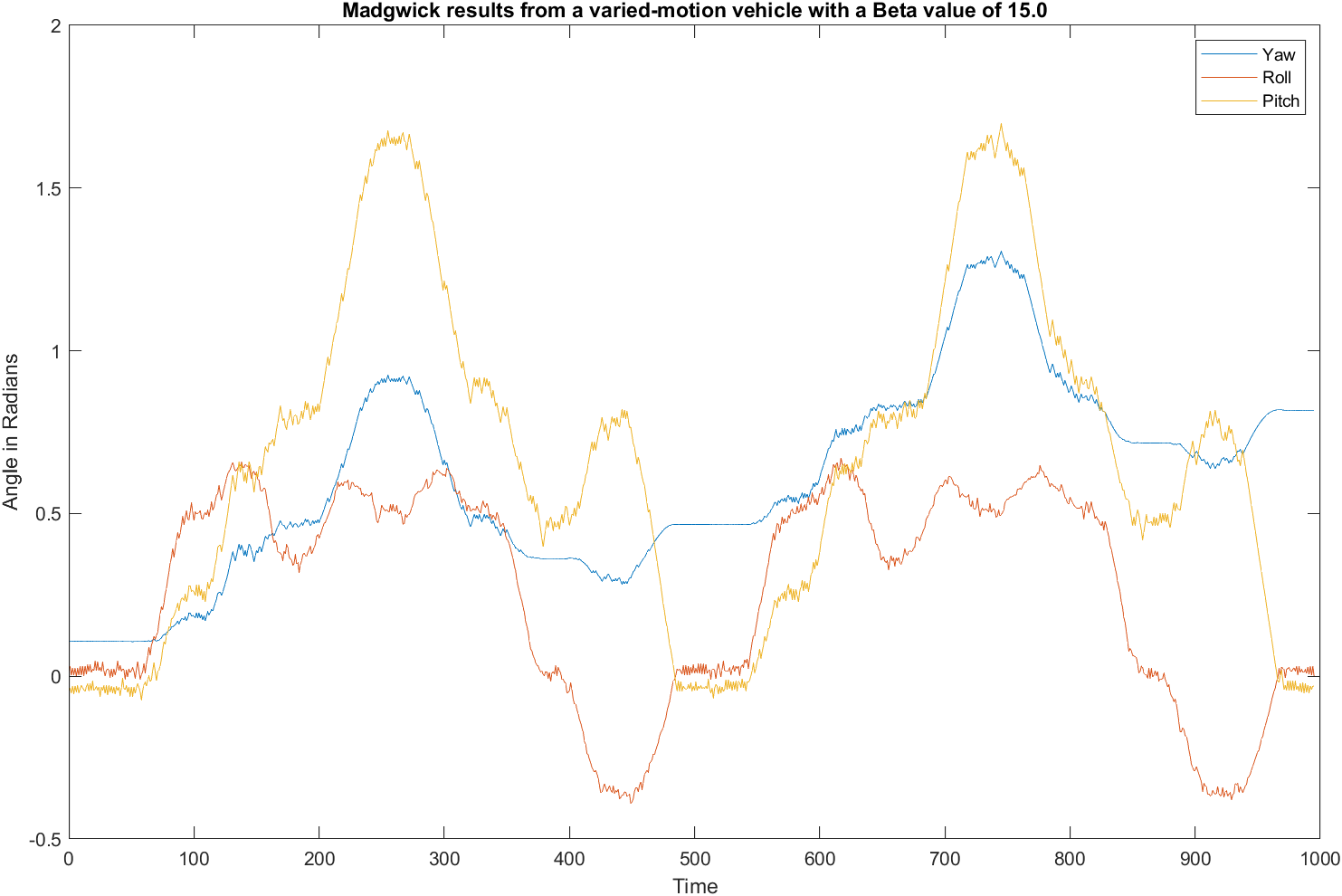


Figure 4‑13 Madgwick results on a varied motion vehicle with Beta value of 15.0

The results show that the Madgwick filter deciphers the euler angles somewhat correctly.  
At t=100, Euler angles are 0.5 (28.65°) for roll and 0.247 (14.15°) for pitch, somewhat close to the 30° and 15° specified. At t=330, the angles are 28.65° and 49.84°, somewhat close to the 30° and 45° specified.

## Option A on a rolling and pitching vehicle: Kalman Filter

Running the Kalman imufilter with default values (gyro noise=-0.3 and accelerometer noise=0.1) across the varied-motion data produced results displayed in Figure 4.13.

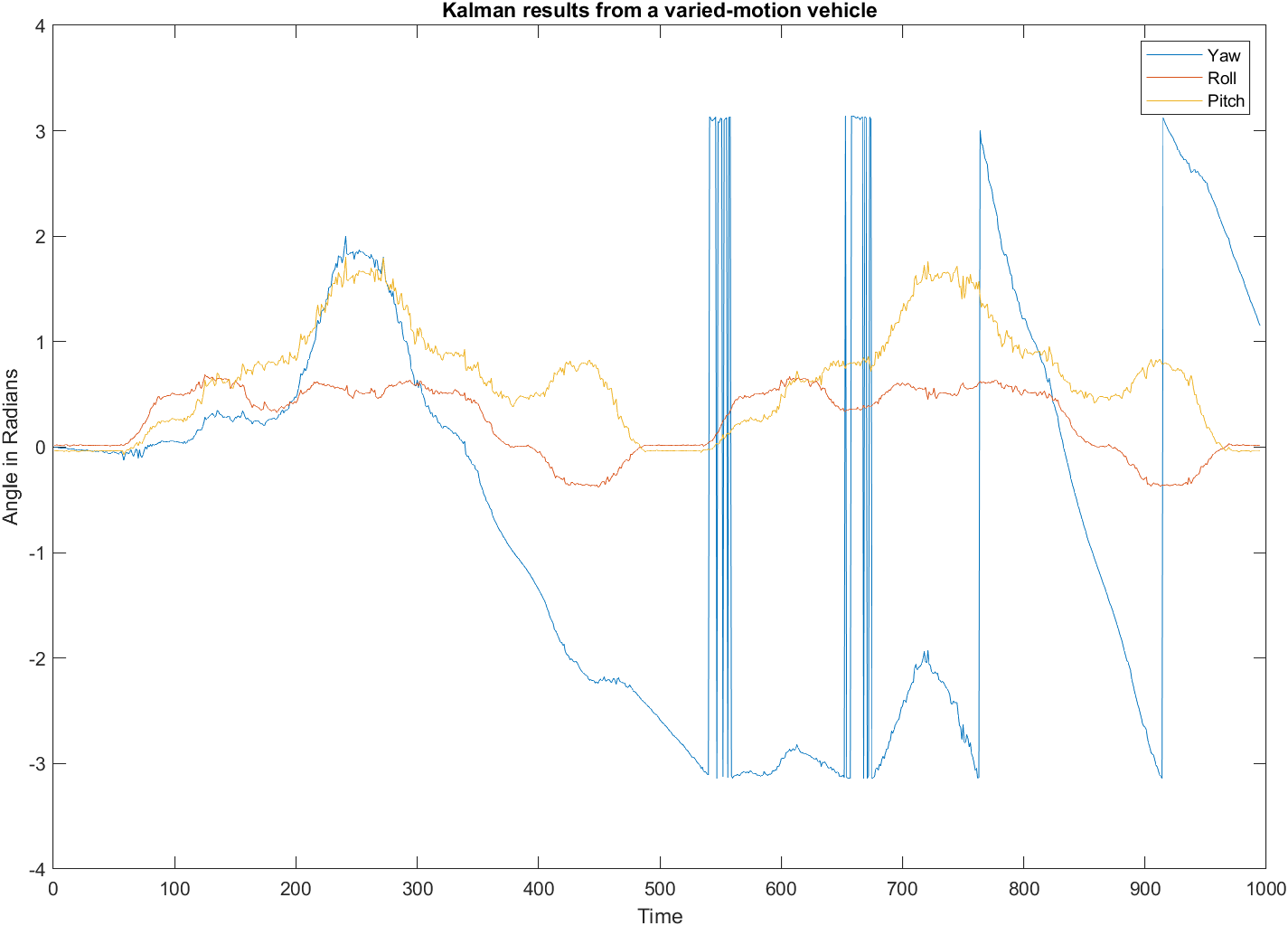


Figure 4‑14 Kalman filter (default settings) results on varied-motion data

Increasing the noise immunity on the filter (gyro noise = 0.6 and accelerometer noise = 0.3) produced better yaw results as shown in Figure 4.14 but showed no improvement on roll and pitch values.

A graph with different colored lines

Description automatically generated

Figure 4‑15 Kalman filter results on varied-motion with gyro noise=0.6 and accel noise = 0.3

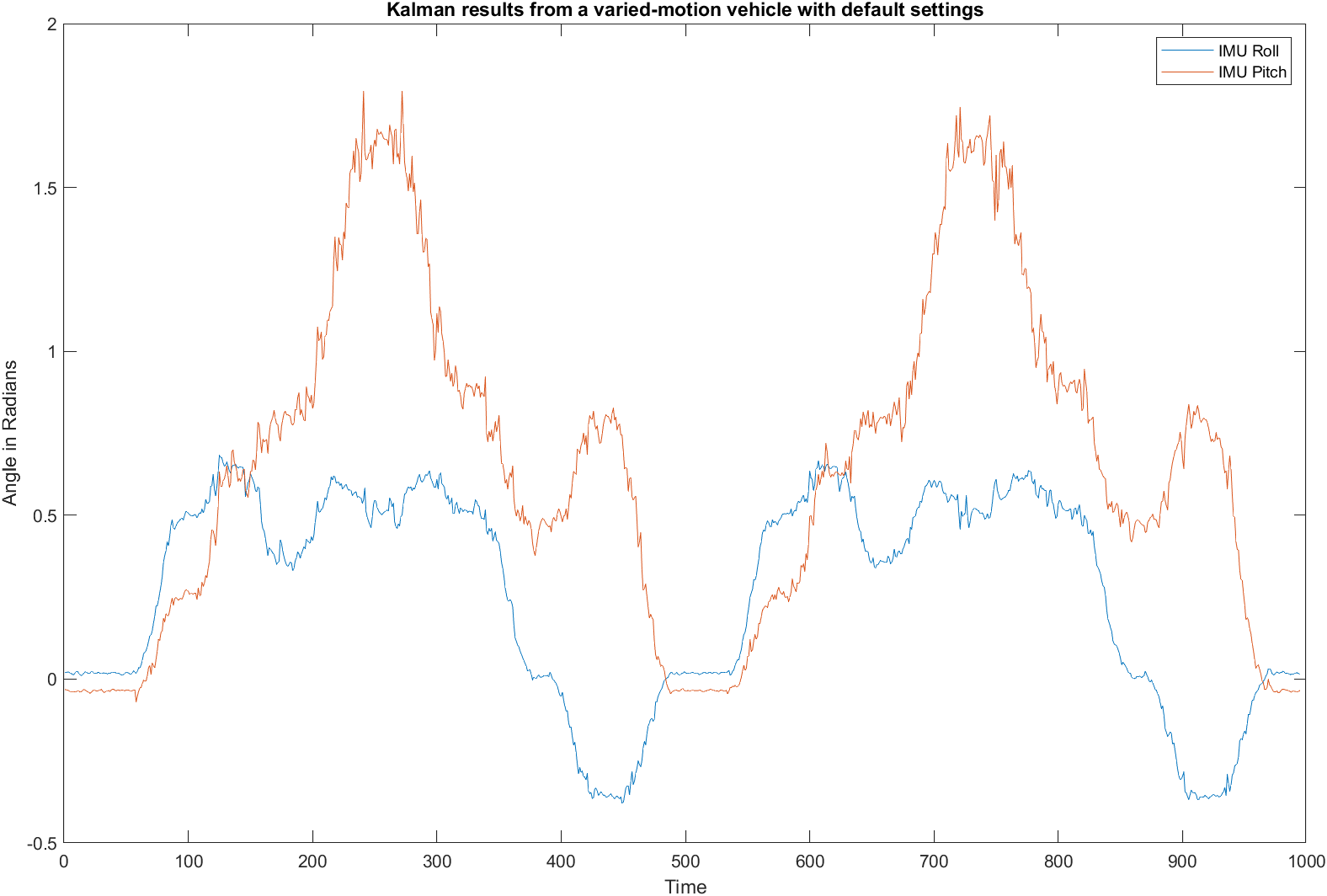
Stripping the yaw value from the graphed output displays the roll and pitch angles in a scale that matches the Madgwick output as shown in Figure 4.15. The output needs some filtering but otherwise tracks the roll and pitch movements of the vehicle. At t=100, Euler angles are 0.503 (28.82°) for roll and 0.26 (14.90°) for pitch, a little closer to the 30° and 15° specified than the Madgwick results. At t=330, the angles are 28.76° and 50.42°, somewhat closer to the 30° figure but further away than the 45° specified, compared to the Madgwick filter. The excessive noise in the Kalman filter results make a direct comparison somewhat difficult however.  
  


Figure 4‑16 Kalman filter results from a varied-motion vehicle displayed without Yaw values

## Option B on a rolling and pitching vehicle: Neural Network

Line 74 in robotdata is start of 10:53:26 – 6476 is last line = 6403 lines per second.  
1001 lines in CM data. 8 samples per second. Difference is 6403/8 = 800.375.  
Line 60 in IMU data is start. Equiv line in robot data is 43334 = 43275 offset.  
  
  
  
wrist1:wrist2  
Roll:Pitch:Time  
0,89.99:5 = 0, 0   
14.99, 60.03:1 = 15:30   
29.99,45.01:1 = 30, 45  
44.98,59.98:1 = 45, 30  
60,-15:1 = 60, 105  
45.01,44.99:1 = 45, 45  
29.99,90:1 = 30, 0  
45.01,119.98:1 = 45,-30  
  
Varied-nodelay=same points with 5 second delay from first position and no delays after that.

The Madgwick and Kalman filters perform as expected.  
The Neural Network architecture performs adequately considering the limited training dataset used.

## Non-trained data of a varied-motion vehicle: Madgwick

## Non-trained data of a varied-motion vehicle: Kalman

## Non-trained data of a varied-motion vehicle: Neural Net

Fitting the Neural Network on untrained data shows a reduction in accuracy as expected.

# Discussion and Analysis

Accuracy of the three approaches was verified against a UR5 Universal Robotics robot arm. This has a worse-case accuracy of 1.15 degrees. The imu chips have a similar accuracy tolerance. The baseboard was screwed directly to the robot arm to eliminate any mounting angle inconsistencies and was constructed of “signboard” which is a plastic-wrapped aluminium, to enforce rigidity.  
  
The robot data is sampled at 6403 times per second. This data was manually “down-sampled” so that robot data samples coincided with the data from the particular imu of interest.  
It is possible that slight errors could have been introduced from the fitting process but these were minimised by manual visual matching of matching data results.  
  
The robot arm is categorised as accurate and is the standard by which the other methods are evaluated but this needed to be pre-calibrated with a spirit level as it was approximately 2 degrees out of true due to being mounted on a wooden bench that had an obvious bow in it (presumably from the weight of the arm). The rigidity of the bench itself (to reduce the impact of fast movements) was insufficient to test rapid robot arm movements.  
  
On a rolling vehicle, the Madgwick, Kalman and Neural-Network results are plotted against the Robot arm movements as shown in Figure 5.1

Figure 5‑1 Comparison of roll-only results

On a pitching vehicle, the Madgwick, Kalman and Neural-Network results are plotted against the Robot arm movements as shown in Figure 5.2

Figure 5‑2 Comparison of Pitch-only results

On a varied-movement vehicle, the Madgwick, Kalman and Neural-Network results are plotted against the Robot arm movements as shown in Figure 5.3.  
  
Figure 5‑3 Comparison of varied-movement results

The Madgwick and Kalman filters perform somewhat similarly with the Kalman having the slight edge in overall accuracy, but computation time of the Kalman filter takes significantly (almost 10 times) longer than the Madgwick filter.

The final neural network architecture is somewhat accurate as well but takes a very long time to generate. This is due to the MLP architecture selected. A Recurring Neural network (RNN) would have a shorter training time but would require more computing power than the Raspberry Pi has available. The advantage of the neural network is that, once trained, the model can be implemented using Tensorflow or equivalent and would require minimal resources to implement.  
Validation time of the untrained data was used to measure the neural network performance in a real-world scenario and this was evaluated to be <TBC>.

# Conclusion and Future Works

## Conclusion

This experiment clearly shows that a neural network can be used to determine roll and pitch orientation details of a vehicle and that multiple Inertial management units are beneficial to improve accuracy.

## Future Work

For future work, the baseboard processing unit should use dedicated SPI lines for increased speed (resolution) and to avoid the switching penalty of multiplexing the IMU data. A Jetson Nano or other unit, capable of utilising TensorFlow models should be used to evaluate the effectiveness of the Neural Network in a live environment. Although directional biases of the individual IMUs were not seen (the errors were consistent across all axes), some of the IMUs should be oriented in differing directions (facing east, west and up, compared to the standard NED orientation, to aid calibration.   
  
The robot arm should be bolted to the floor (as I believe was previously the case at the University of Canterbury) to prevent the mounting table from moving when rapid robot arm movements are attempted. The robot should be oriented in the home position and a bracket designed to mount the baseboard so there is no need for rotation operations on the robot pitch data.

# 

# Appendices

## Appendix 1 – Code

All code can be obtained from https://github.com/BratNZ/Thesis

## Appendix 2. Calibration results.

Table 7.1 IMU Error Coefficients produced from initial calibration (rounded to 8 decimal places)

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| IMU | GyroX | GyroY | GyroZ | AccelX | AccelY | AccelZ |
| RR | -0.02998955 | 0.01596670 | 0.00715132 | 0.00078995 | -0.01058559 | -0.02925765 |
| FR | -0.03219639 | 0.00790274 | -7.2477796985e-05 | -0.00159294 | 0.01550039 | -0.01817877 |
| CM | 0.023254980 | 0.00284742 | -0.00660733 | 0.01240663 | 0.0155684 | -0.03045218 |
| FL | 0.008131502 | -0.00708547 | 0.00312161 | -0.00665329 | -0.01244544 | -0.01997862 |
| RL | -0.00307724 | 0.00518083 | -0.00114486 | 0.0027521 | 0.0128008 | 0.00237755 |

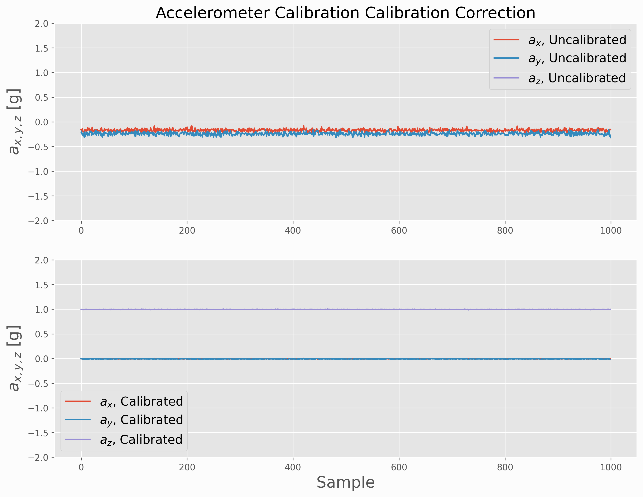
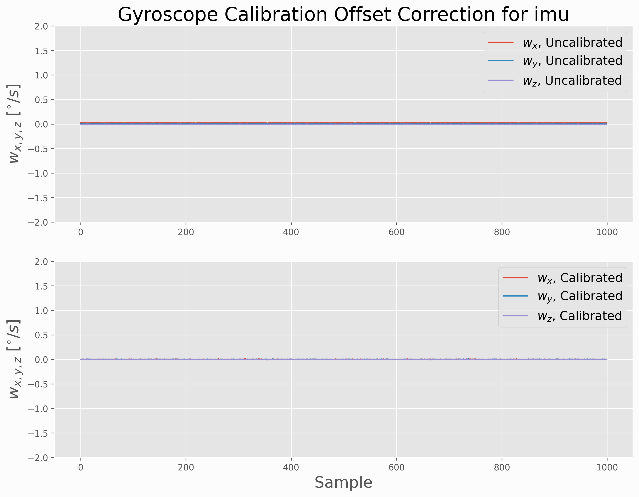
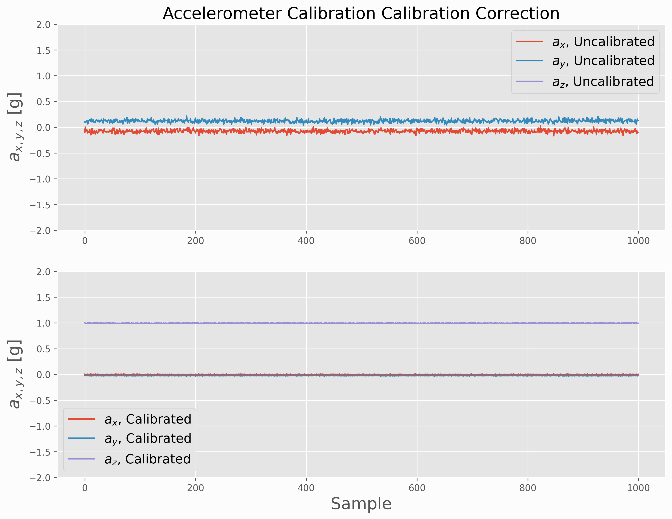
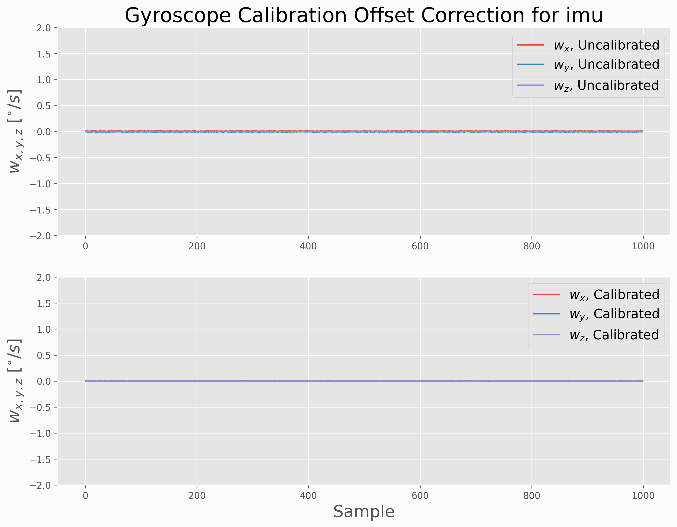
  


Figure 7‑1 IMU Calibration graphs for Central Camera IMU

Figure 7‑2 IMU Calibration graphs for Front Left IMU

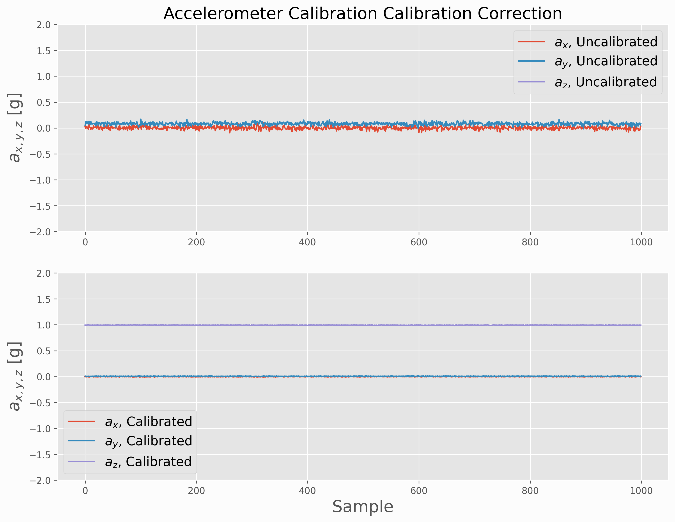
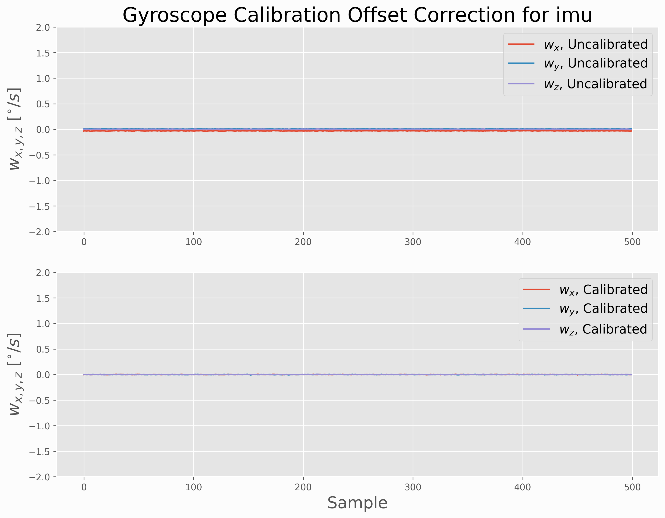


Figure 7‑3 IMU Calibration graphs for Front Right IMU

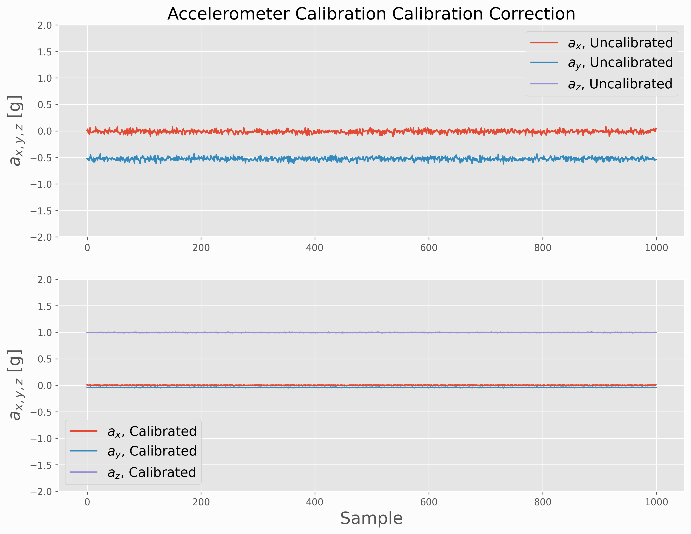
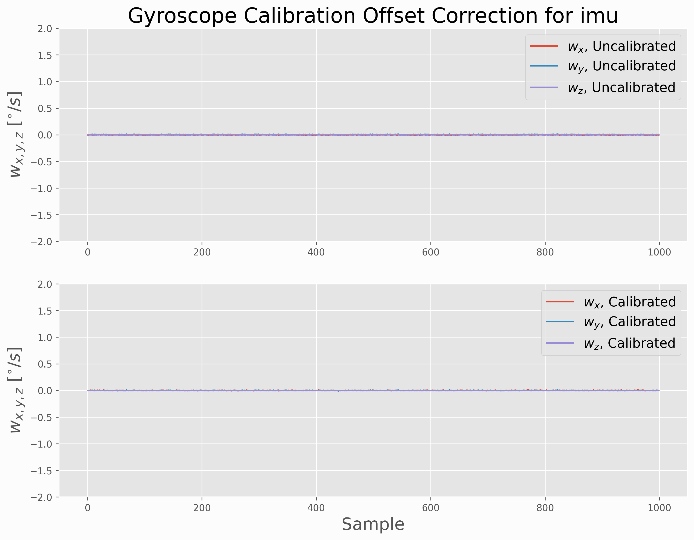


Figure 7‑4 IMU Calibration graphs for Rear Left IMU

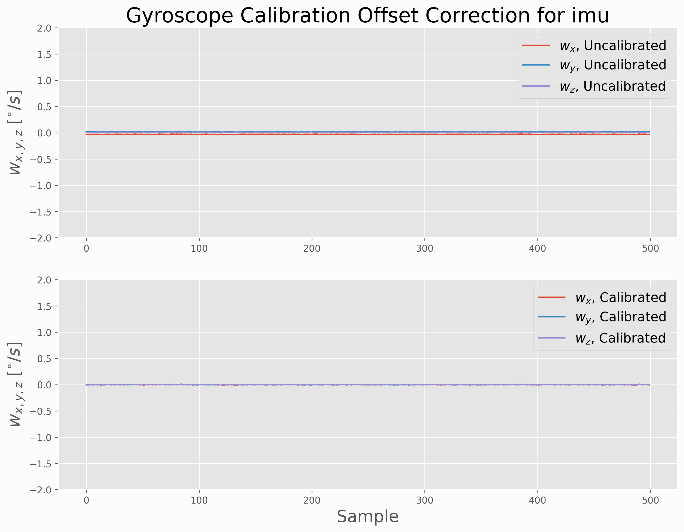
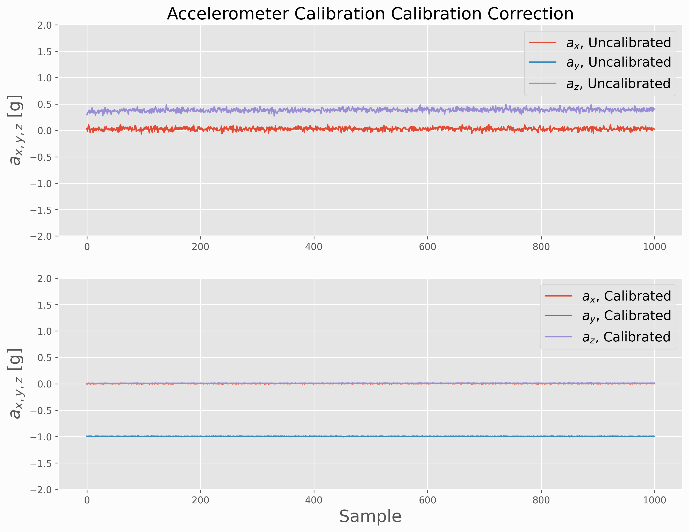


Figure 7‑5 Figure IMU Calibration graphs for Right Rear IMU

## Appendix 7.3 Electrical Characteristics of IMU-29048 IMU

|  |  |
| --- | --- |
| Digital Output | I2C  SPI |
| VDD Power Supply / V | 1.71 to 3.6 |
| VDDIO I/O Power Supply / V | 1.71 to 3.6 |
| Gyro FSR | ±250/500/1000/2000 |
| Gyro Sensitivity Error | ±1.5% |
| Gyro Rate Noise | 0.015dps/√Hz |
| Accel FSR | ±2/4/8/16 |
| Accel Sensitivity Error | ±0.5% |
| Accel Noise | 230μg/√Hz |
| Compass FSR | ±4900μT |
| Pressure Sensor Relative Accuracy |  |
| Pressure Sensor Noise |  |

# Chapter 8

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