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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Image stabilisation is desired for efficient identification of objects in the path of a self-driving vehicle. The gyroscope and accelerometer of an inertial measurement unit (IMU) can be used to derive the movement of a vehicle, which can then be used by a rotation matrix to compensate for this movement but a gyroscope has inherent “drift” errors, and while the accelerometer of an IMU is more accurate, it has a slower response time which reduces the detection rate.   
Kalman filters are often used to fuse the gyroscope and accelerometer data to reduce the effects of drift, noise and other gaussian-based errors but these are computationally intensive for the sort of lightweight processor that a radio-controlled car could be expected to power. A complementary filter is a simpler and less processor-intensive solution.   
  
This project compares complementary and Kalman filter operation with a neural network when performing sensor fusion and investigates if using a neural network of multiple 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.

**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 Malcolm 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 ground vehicle (UGV or rover) is required, 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 presented and the research objective is outlined.

### 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 (Swain 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 (Swain 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).  
  
To track animal movement, a Global Positioning System (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.

The main problem with gathering data from an animal that moves is efficiently transmitting that data back to the farmer. In the following sections various data gathering methods are discussed and the rationale for using a rover for data capture is outlined. Besides battery life and route planning, the next major issue of using a rover on alpine terrain is object avoidance, and various sensor types are presented and the reason for using a camera as the main sensor (with assistance from others) is presented. One issue effecting the use of a camera is image stabilisation, especially when a rover could be travelling at high speeds. Various image stabilisation methodologies are presented and the utilisation of IMUs is outlined.

### Data Gathering Methods

There are three main methods available to collect data from a remote location.   
Radio Frequency (RF), a data mule (autonomous device travels to sensors to collect data) and a hybrid solution of these.

#### **1.1.2.1 Radio** frequency data collection.

Possible radio frequency (RF) implementations include satellite (De Sanctis et al., 2016) , cellular service (Gaddam & Rai, 2018) , dedicated radio links such as WiMAX (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).  
These systems transmit the signals from the sensors to either a central location (this design is called “hub and spoke”) or in a form of ““ 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, 2023; 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 Back haul

Long range radio frequency systems include satellite, cellular service, dedicated radio links and Long-Range Wireless Area Network (LoRaWAN). The strengths and weaknesses of these systems in an alpine farmland context is discussed in this section.  
  
Satellite systems need a clear line of sight to a minimum of 4 satellites greater than 15 degrees above the horizontal plane for GPS location 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 sensors and a back-end infrastructure, which aids simplicity.   
Disadvantages are that satellite data transmission is expensive as each animal would need a satellite transmitter and data plan. Confidentiality of data would also need to be considered.   
The use of GPS is free and transmitters are ubiquitous and are low-cost so satellite transmission should be reserved for GPS location data only.

Cellular systems.

Cellular technologies (4G, 5G). Public cellular technology support in the high country is sparse although recent OneNZ announcements are supplementing cellular support with the use of Starlink satellites, to be released in 2025 (OneNZ, 2023a).   
  
Current fourth generation (4G) coverage is possible in rural high country but there are pockets of no coverage from commercial providers (OneNZ, 2023b; Spark, 2021). Coverage would need to be evaluated and confirmed on each site.  
Purchasing a subscriber identity module (SIM) card for each animal would quickly become expensive, even without considering potential damage from animal activity, but like GPS data, does reduce the architecture down to sensor devices and the cloud.  
It is possible to utilise generic consumer SIM technology to perform connectivity but the customer would be paying for voice capability where that is not required.  
  
Fifth generation (5G) cellular technologies (Cat-M1, LTE-M, Narrowband-IoT) 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 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, described in Table  
Narrowband-Internet of Things (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.

Table 1.1 Commerical Long-range IoT radio standards compared.

|  |  |  |  |
| --- | --- | --- | --- |
|  | LTE Cat M1 | NB-IoT | GSM-IoT |
| Deployment | In-band LTE | In-band & Guard-band LTE, standalone | In-band GSM |
| Coverage\* | 155.7 dB | 164 dB | 164 dB with 33dBm power class  154 dB, with 23dBm power class |
| Downlink | OFDMA,  15 KHz tone spacing, Turbo Code,  16 QAM, 1 Rx | OFDMA,  15 KHz tone spacing,  1 Rx | TDMA/FDMA,  GMSK,  PSK (optional), 1 Rx |
| Uplink | SC-FDMA,  15 KHz tone spacing Turbo code,  16 QAM | SC-FDMA,  15 KHz and 3.75KHz tone spacing,  Turbo code | TDMA/FDMA, GMSK and 8PSK (optional) |
| Bandwidth | 1.08 MHz | 180 KHz | 200kHz per channel. 600KHz to 2.4MHz |
| Peak rate (DL/UL) | 1 Mbps for DL and UL | DL: -50 kbps  UL: -50 kbps (multitone) : 20 kbps (single tone) | For DL and UL (4 timeslots):  70 kbps (GMSK),  240kbps (8PSK) |
| Duplexing | FD & HD (type B), FDD & TDD | HD (type B), FDD | HD, FDD |
| Power saving | PSM, ext. I-DRX,  C-DRX | PSM, ext. I-DRX, C-DRX | PSM, ext. I-DRX |
| Power class | 23 dBm | 23 dBm | 33 dBm or 23dBm |

Dedicated link RF options

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.   
  
SigFox is a proprietary system where devices connect to base stations which connect to each other via point-point links (maximum range of 50km) 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.  
  
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 is a proprietary protocol owned by Semtech. 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, Spark concentrate LoRaWAN in the main urban centres (Spark NZ, 2023), so 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 4G or 5G satellite protocols at an additional cost and complexity.

Dedicated radio links are a possible solution but 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 1.2 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 and capacity | Range and data rate | Data rate, capacity and range |
| Recommended Applications | Where Video/Voice are required | Where Images/Voice are required | Where Images are required | For small datasets generated hourly. |
| Farm Use | Not ideal | Ideal for large datasets if available | Ideal for medium sized datasets if available | Ideal for small datasets if available |

##### Short Range RF options

ZigBee is based on the IEEE standard 802.15.4 (Baronti, P Pillai, P Chook, V.W.C Chessa, S Gotta, A Hu, 2007) for small personal LAN communication with a range from 10-100m (for the standard variant) or 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 (LOS) communication 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. Zigbee is a possible solution for communication between cattle and to a very local transmission site but other devices will be needed to transmit data back to the farmer.  
  
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.

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. 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. As such, Wifi HaLow is only possible for cattle monitoring. 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 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.

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 in designing a system. 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.  
  
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).  
  
LoRaWAN can be used as a short haul system but the other systems are more cost-effective, albeit with reduced range.

Table 1.3 Short range communication protocols compared

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Parameter | RFID | ZigBee Default | ZigBee Long Range | BluetoothLow Energy | BluetoothVersion5 | 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 and 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 |
| Farm use ideals |  | Not ideal | For small datasets only | Not ideal | Only useful for animal to collector site use | Not ideal | Ideal but imported cards may be expensive and not supported in NZ |

The choice of short range RF solution for an alpine farm will depend on the amount of data transmitted and the number of animals. Wifi HaLow is an interesting option but it’s cost and lack of support (at present) makes recommending Bluetooth V5 an easy choice.

Table 1.4 Communication protocol options available on a range of microcomputers

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| 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 |

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

#### 1.1.2.2 Data Mule

To avoid the monthly costs and possible infrastructure investments in RF backhaul technology, an autonomous 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 (humorous) ethernet over avian carrier protocol (Waitzman, 1990). At the time of writing, this approach would incur significant range limitations due to current battery technology 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 “drone”) 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 to visit each animal however these face issues of more difficult route planning and obstacle avoidance concerns. As such, using a rover data mule to visit individual animals is not addressed in this project.  
  
1.1.2.3 Hybrid of RF Short-Range and Data Mule solution

Beef cattle tend to revisit feed and water lots (Johnstone-Wallace & Kennedy, 1944; Martina et al., 2015) so a hybrid of the RF short-range option and a rover-based data mule could be implemented where cattle visit a solar-powered data-aggregation feed/water site and transmit their data by one of the short range RF options (Bluetooth version 5 for example) (Jawad et al., 2017) and then, a rover data mule 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. Each data-collection site’s short-range RF 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

The main difficulties in using a rover as a data mule 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 (Nguyen-Huu & Titus, 2009), Battery life (Hall, 2021; Zogopoulos, 2021) and Data storage methodologies and systems are improving all the time so the current limitations of these will not be addressed as it is assumed they will be alleviated in the near future.   
Route planning and obstacle avoidance are somewhat related as an efficient route planning system must also address any potential obstacles.  
The route planning problem is generally treated as an NP-Neighbourhood solution (Ab Wahab et al., 2015; Koenig et al., 2004; Sugihara & Gupta, 2011) however the presence of potential obstacles requires that the route-planning system adjust a planned route dynamically to account for a new localised route to avoid the obstacle and continue (Masehian & Katebi, 2014).   
To avoid obstacles the rover must first be able to detect them, and the following section outlines possible detection sensors and their limitations.

### 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 vegetation 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 passive 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 1.1 Obstacle detecting Sensor Types (Image from author).

Radio detection and ranging (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 ultra-wideband (UWB) 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 (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 and sensing rate. The wavelength is approximately 4mm and so can miss some narrow surfaces such as a narrow bush branch or a fence wire, 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). (Kleeman & Kuc, 2008). SONAR’s main advantages are price and that, being sound based, it is immune to visibility issues such as dust, fog and night.  
  
Light detection and ranging (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 (FIR) 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 (typically active systems) are more effected by environmental conditions, especially solar radiation from the sun.

FIR 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 successive image frames 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.

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.   
  
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.

#### 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 (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.)

Table 1.5 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) |

A very high resolution camera is the suitable solution, supplemented with a non-visual sensor such as SONAR or RADAR, however this will come with its own benefits and limitations.  
  
Camera-based solutions to recognise obstacles

Cameras are often used in industry to perform obstacle detection as they provide many advantages.   
To provide obstacle detection a video camera is used as differences between successive image frames can be analysed to determine if a recognised object is getting closer or not.  
  
A single video image is a matrix of pixels (a single piece of information in the image), with each pixel having a combination of three luminance values, each measuring the luminance value of a particular colour. Pixels are normally manufactured in Red, Green and Blue variants and these systems are discussed in this report. An individual image can be represented as a matrix of values as per Table 1.5. The resolution of an image depends on how many pixels are in the image and the size of the number storing the luminance values.

Table 1.6 Simple representation of a single video image.

|  |  |  |  |
| --- | --- | --- | --- |
|  | Horizontal Pixel  1 | Horizontal Pixel  2..(N-1) | Horizontal Pixel  N |
| Vertical Pixel 1 | Red, Green and Blue luminance values | Red, Green and Blue luminance values | Red, Green and Blue luminance values |
| Vertical Pixel 2..(N-1) | Red, Green and Blue luminance values | Red, Green and Blue luminance values | Red, Green and Blue luminance values |
| Vertical Pixel N | Red, Green and Blue luminance values | Red, Green and Blue luminance values | Red, Green and Blue luminance values |

Obstacle identification is generally based on edge detection of an image – 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 industry-utilised 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 multi-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.

The main problem of using any form of edge detection algorithm is the quality of the image.  
An ideal image has no noise, and perfectly describes the scene it represents. In the real world, images are of a limited pixel and luminance value count and the lens used to capture the light introduces distortions of scale in the image. The image may consist of extremes of light that the imaging system may not perfectly capture (commonly called over and under exposure). Rain, snow or other environmental conditions may also reduce image quality. These are all well-known problems and many different solutions exist to reduce their impact on image quality.  
  
One external issue impacting quality that is particularly relevant to a rover is image stabilisation.

### Image stabilisation

As a video stream is a successive stream of images, the motion of objects around a vehicle can be determined by locating an object (often called a “feature”) in an image 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) are 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.   
  
Image stabilisation works by compensating for the movement of a vehicle by recognising that movement and applying a counter-movement in the opposite direction. As such, some image resolution is lost as the resulting usable image is of smaller dimensions than the original and the system will not work if the movement results in an entire frame being out of position compared to the previous frame.  
  
There are two main types of image stabilisation systems; Optical Image Stabilisation (OIS) and Digital Image Stabilisation (DIS) or a hybrid of these two approaches. We will concentrate on the first two methods.  
  
1.1.5.1 Optical image stabilisation (OIS)  
  
One solution to the problem of image stabilisation is to use optical image stabilisation (OIS) where an 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.

1.1.5.2 Digital Image stabilisation (DIS)  
  
Digital image stabilisation uses computers to perform the image stabilisation.  
Three main methods exist. Feature Mapping and Sensor Fusion or a hybrid of these methods.

##### DIS Method One. Feature Mapping

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 also 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, mathematical rotational and/or translational matrix operations are used to apply this vector in the opposite direction to counter the effects of the movement.

##### DIS Method 2. Sensor Fusion

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 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 used with feature tracking are then applied. The most common sensor utilised with this approach is using an inertial measurement 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). These angles are commonly called euler angles. Note that the convention of x,y and z axes 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, but here, we will use the terms demonstrated in Figure 1.2.

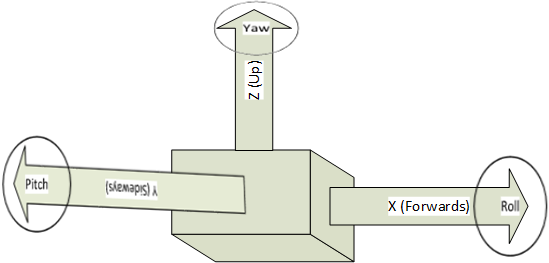


Figure 1.2 Diagram of conventional roll, pitch and yaw angles (Image from Author).

The mathematical process to convert between gyroscope angles to Euler angles incorporates integration which introduces a cumulative error, the size of which depends on the number of samples. Along with this problem is the issue of gyroscope drift, where the gyroscope values deviate over time due to temperature variances, gyroscope tolerances and external disturbances such as the jostling of a moving vehicle. The results of these two errors can be seen in Section 4.   
The general process of using an IMU accelerometer to measure euler angles is expressed in the following mathematical equations.  
At rest, gravity is the only acceleration acting on the IMU, and assuming it is mounted so the z axis points straight down, the acceleration matrix is:

Equation 1.1 Acceleration at rest where g=9.81m/s2.

The acceleration in a tilted frame is

Equation 1.2 Acceleration on a tilted frame

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:

Equation 1.3 The mathematical relationship between level and tilted frames.

Solving for pitch and roll, we get:

Equation 1.4 Mathematical equations for pitch and roll

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, as the camera and front IMUs are mounted close to an electric motor on a steel chassis, the magnetometer readings are not utilised.

To measure orientation using an accelerometer, an initial orientation must be known and then measurement values are integrated over time as acceleration is differentiation of speed. Integration of any errors will lead to increasing error components in the calculated value.

Once the roll and pitch values are known, a rotation matrix can apply these angles to our video frame data 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 red-green-blue-depth (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 is present in this project, requiring 6DOF.  
Wiriyaprasat and Ruchanurucks (Wiriyaprasat & Ruchanurucks, 2015) 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 (ILSE) 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 the approaches listed above only considered single IMU units.

##### DIS Method 3. Hybrid of Feature mapping with sensor fusion.

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. A direct approach to reduce the impacts of large jostling movements is to utilise a wide point of view lens such as a “fisheye” so a feature will stay in the frame even with large movements however this introduces significant lens distortion which will need correction in software.



Figure 1.3 Fisheye Lens capture example. Copyright free Image from (Fpatrocini, n.d.)

The fish-eye lens solution is a good solution for a fast-moving rover and is recommended for use in a production system but will not be evaluated in this experiment for simplicities sake.

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.

It is possible that a Neural Network could perform this form of regression task of both single and multiple IMUs.  
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

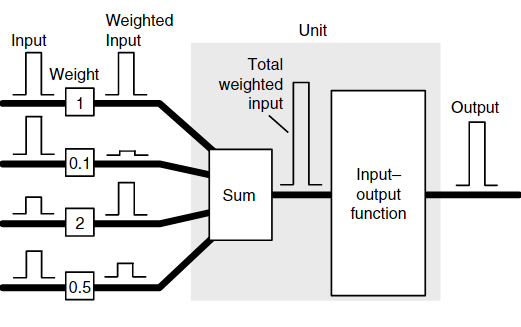


Figure 1.4 Neuron construction (unit part of the diagram). Image from (Samarasinghe, 2006).

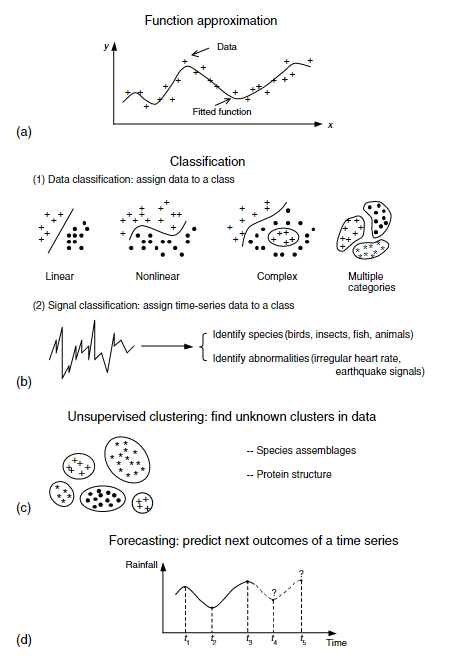
One of the inputs is usually given a value of 1 and called a bias input. This input is used to account for output effects that are not accounted for by the other inputs.  
  
Training data is used to train a network and must consist of input values and associated correct output values. Training involves 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 1.5 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

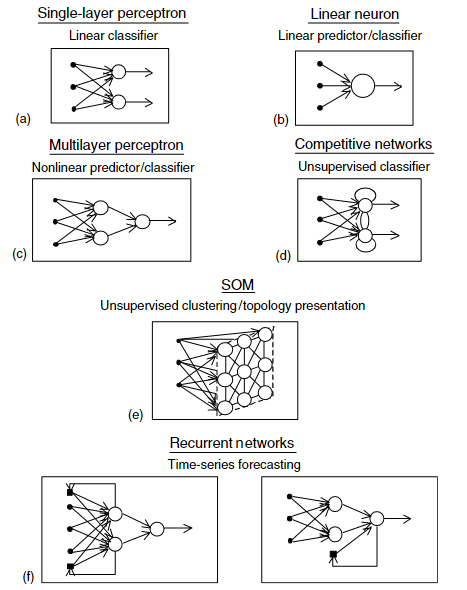


Figure 1.6 Some neural network topologies: (a) single-layer perceptron, (b) linear neuron, (c) multilayer perceptron, (d) competitive networks, (e) self-organising feature maps and (f) recurrent networks. Image from (Samarasinghe, 2006)

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 valid responses are included in the training data. 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 is initially selected.   
A Recurrent Neural Network (RNN) is a network designed for recognising patterns over time. It is a different design than conventional neural networks where weighted inputs are applied to a function which then passes the function result to the next stage, in that outputs from some of the neurons are fed back into the inputs of the same neurons as a feedback mechanism. These networks provide a localised “memory” feature in the feedback-equipped neurons which makes RNN networks excel at relational problem solving tasks such as language processing but seemed excessive for a relatively simple regression operation.

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. There are two main parameters of the network that are examined to ascertain accuracy. MSE is the mean square sum of any differences that appear between the input and the output of a neural network, compared to the expected training results. The MSE gives a measure of how accurately the network is able to reproduce a single set of output values from the input values. The Pearson Coefficient, R, is used in a neural network to measure how well the neural network understands the entire problem and reflects the accuracy of the trained algorithm across all inputs and outputs.  
  
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 measurement unit.  
A secondary objective is to determine the least number of inertial measurement units required to provide a significant measurable improvement.  
A tertiary objective is to determine the most basic neural network architecture required to provide acceptable (above 90%) accuracy, when calculating the Euler angles used to rotate an image.

## 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 a place for Appendices and Chapter 8 contains a list of 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 mathematical processing artifacts (integration) and gyroscope data has inherent drift issues. Various methods have been proposed to counter these concerns.   
  
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.)  
  
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).   
To counter gyroscope drift and bias errors, accelerometer arrays have been proposed (Madgwick et al., 2013) but these lack real world testing and implementation.  
  
  
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.   
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 only for slow and controlled ranges of motion, and so, is not suited for a bouncing vehicle.  
  
Madgwicks IECF6 algorithm is used as the control factor in this project. This filter algorithm uses quaternion representations of angles internally to avoid the singularities caused by angles approaching π/2 radians. A single beta weighted-gain value acts as a fusion factor in a complementary filter, feeding accelerometer data into the gyroscope data to compensate for gyroscope drift. A gradient-descent algorithm enables performance at low sampling rates but, internally, the lowest sampling rate is recommended to be 10 Hz. The sampling rate of the experimental equipment averages at 8.3 Hz so it is expected that the Madgwick filter may not perform as well as the Kalman.  
  
The standard MATLAB Kalman-based imufilter is used as a comparison with the Madgwick results.   
  
Multiple IMU solutions have been proposed before (see above) but none have suggested using a neural network across multiple IMUs. The concept of a neural network has been covered in the introduction.  
Using a back-propagating or Levenberg-Marquardt (LVM) trained supervised neural network with multiple IMUs should effectively compensate for drift and other errors present in a single IMU implementation and these are models implemented in this project. Due to the computation requirements of a neural network, it makes most sense to apply the neural network directly to sensor readings, rather than complementing a filter algorithm, as the neural network should be able to determine the relationships.  
  
In Chapter 3, the experiment design and methods are outlined, in Chapter 4, the results from these experiments are detailed and discussed, with analysis of these in Chapter 5 and conclusions reached in Chapter 6.

# Method

In this chapter, the method is outlined. The design is presented first with the implementation setup and calibration details following. Details of the experiments undertaken will then follow. All angles are expressed in radians unless otherwise mentioned.

The primary objective is to determine whether multiple inertial measurement units in conjunction with a neural network can improve image stabilisation of a camera, compared with a single inertial measurement unit.  
  
To address this objective an experiment was designed where multiple inertial management units (IMU) were attached to a rigid board as shown in Figure 3.1. A single IMU in the centre at the front provides data as a typical single IMU system would. Four further IMUs placed at each corner provide multiple IMUs for comparison against this single central IMU. To provide controlled motion of the IMUs a Universal Robotics UR5 robotic arm is used to manipulate the board to known angles.

A diagram of a computer

Description automatically generated

Figure 3.1 Baseboard diagram showing components (Image from Author).

In Figure 3.2 a method flowchart is presented which outlines the process followed.

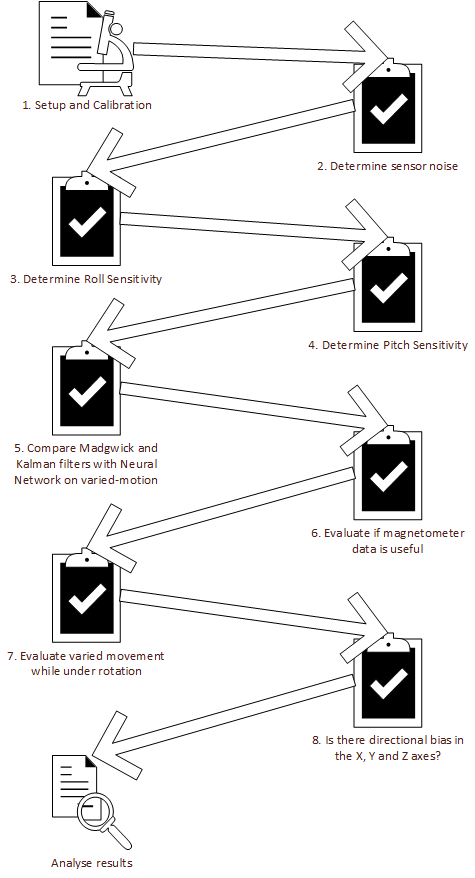


Figure 3.2 Method Flowchart (Image from Author)

The experiment setup and calibration process are described in Section 3.1. The experiments are described in Section 3.2, including the Madgwick and Kalman filter configuration and neural network setup and training.

## Experimental Setup and Calibration

To determine if a neural network with multiple IMUs is more accurate than with a single IMU, a replica of a vehicle chassis is constructed and the mounted IMUs are moved in various angles by a robotic arm (to provide a “ground truth” of measurements). IMU data is captured and then processed by the two filters and the neural network to gather Euler angle data which is compared against the robot arm movements.  
  
A baseboard chassis is constructed of Signboard (two layers of plastic sandwiching an aluminium panel) to provide rigidity so that all IMUs record the same movements (Figure 3.1).  
  
Mounted to the baseboard is a Raspberry Pi connected to five Sparkfun IMU-20948 IMUs via a Sparkfun TCM9548A I2C multiplexor as shown in Figure 3.1. (Details of all equipment used in the experiments can be found in Appendices 3 and 4). The TCM9548A multiplexor is required as ICM-20948 IMUs only have two configurable I2C addresses. For single IMU data collection, the front centre “camera” IMU is used. For “Front 3” IMU data collection, the front three (“FL”, “FR” and “Camera”) IMUs are sampled and all IMUs are sampled under “All IMU” experiments.  
  
A Universal Robotics UR5 robotic arm provides the “ground truth” of correct angles that is used to verify the filter and neural network results.

Data capture is managed by a laptop connected to the both the robotic arm and the Raspberry Pi by an unmanaged one gigabyte ethernet switch. A python script (GetRobotData.py location is specified in Appendix One) uses the ut\_rtde puython module to connect to the robot arm over ethernet and polls the arm for position data.   
  
Various movement experiments are performed on the robotic arm and IMU and robot arm data is captured as outlined in the method process of Figure 3.2 with more detail in Table 3.1.  
  
The data for all IMUs is captured even though the initial experiments only utilise the camera IMU data to mitigate against artifacts brought in by measuring the IMUs differently when later experiments are undertaken. Outlying data is kept to emulate real world performance (as removing this data could be problematic to differentiate from vehicle movement in production).

Details of the Madgwick and Kalman filters and the neural network model will follow the experiments section.

### Calibration.

This section outlines the calibration of the IMU devices and outlines how the IMU data will be synchronised to the robot arm data. The contents of all scripts and configurations can be found in the github location mentioned in Appendix 1. Detailed specifications of the equipment can be found in Appendices 3 and 4.

The UR5 robot arm needs to be calibrated first as the UR5 robot joint angles showed 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 centre point (TCP) sensors on the tool section of the arm initially showed true values of the pose compared to the spirit level however so the TCP sensors were used first in initial measurements. When robotic movement was performed, it became evident that the TCP sensors calculate positioning based on weight and size of the tool mounted on the arm which introduced some subtle errors on the baseboard, depending on orientation of the board. The actual joint angles of the arm components were used instead to obtain direct angular positions and angles altered in math if the joint angles were required to be mounted at non-zero angles in order to get full range of motion of the chassis.  
  
When operating the robot, it was noticed 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 centre point (TCP) sensors have a worst-case accuracy error of 20mm in positioning and 1.15 degrees in orientation. These are worst-case values, however, and the robot operated well within these limits.  
  
The decision to use a robot arm meant that the baseboard was screwed directly to the robot arm as mounting the actual testing vehicle would have been significantly more challenging to avoid the size of the vehicle limiting the range of movements the robot arm can travel. Figures 3.3 and 3.4 show the robotic arm with the baseboards mounted in the starting positions for the experiments.



Figure 3.4 Robotic Arm position showing mounted baseboard for roll and pitch experiments

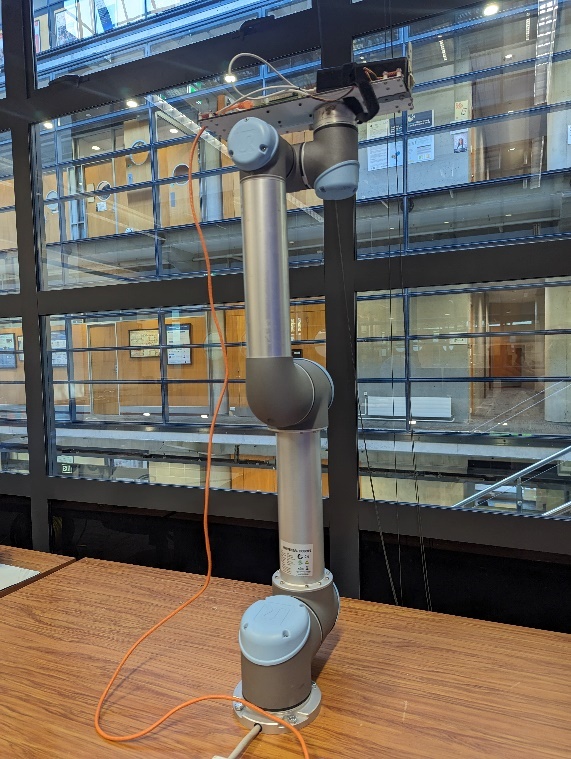


Figure 3.5 Robotic Arm position showing mounted baseboard for all other experiments

The IMU’s gyroscopes and accelerometers are calibrated using static measurements at various positions of π/2 radians on all axes, using recorded gravity as a control measurement. (ie Tilting the board by 90 degrees in all directions). The calibrate.py program is used to undertake this calibration and the resulting offset values entered into the imudata.py IMU data-capture script so that caputured data has the calibration offsets applied as data is recorded.

The two dataset (IMU and robotic arm) measurements are to be manually synchronised.   
To undertake this, when an experiment is performed, data from the camera IMU and the robotic arm should be visually investigated to determine when movement is first detected. The two elapsed time positions can be entered into the appropriate MATLAB command script for that experiment and the MATLAB processing steps can then be re-applied to the data to achieve alignment.

It is tempting to just align the data samples with an offset based on sample position rather than time, but, as is the nature of general-use multitasking operating systems, the data sampling rate will not be consistent and results similar to Figures 3.1 to 3.6 will be seen. Figure 3.1 shows the result of very poor alignment. Figure 3.2 is the result of aligning data over the entire dataset which appears to be acceptable over the entire dataset but Figures 3.3-3.6 show the inevitable variations in timing of this approach.

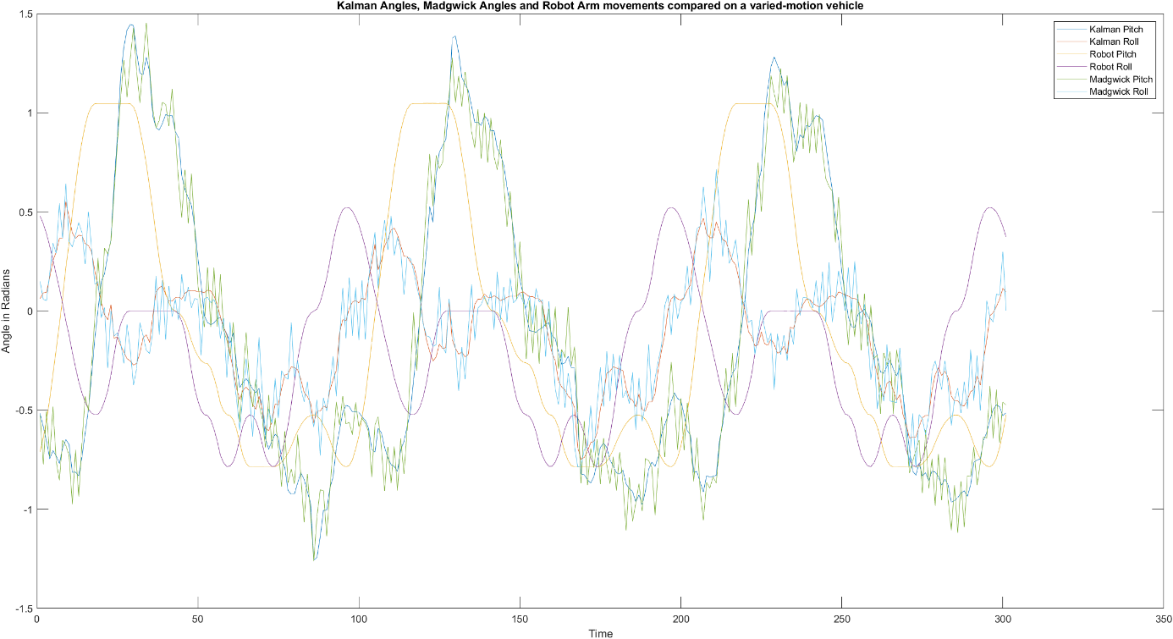


Figure 3.6 Sub-optimal alignment plot from t=1000 to t=1300 from a dataset of 4999 values

A graph showing a sound wave

Description automatically generated with medium confidence

Figure 3.7 Overall “best-fit” alignment plot showing OK alignment at this level

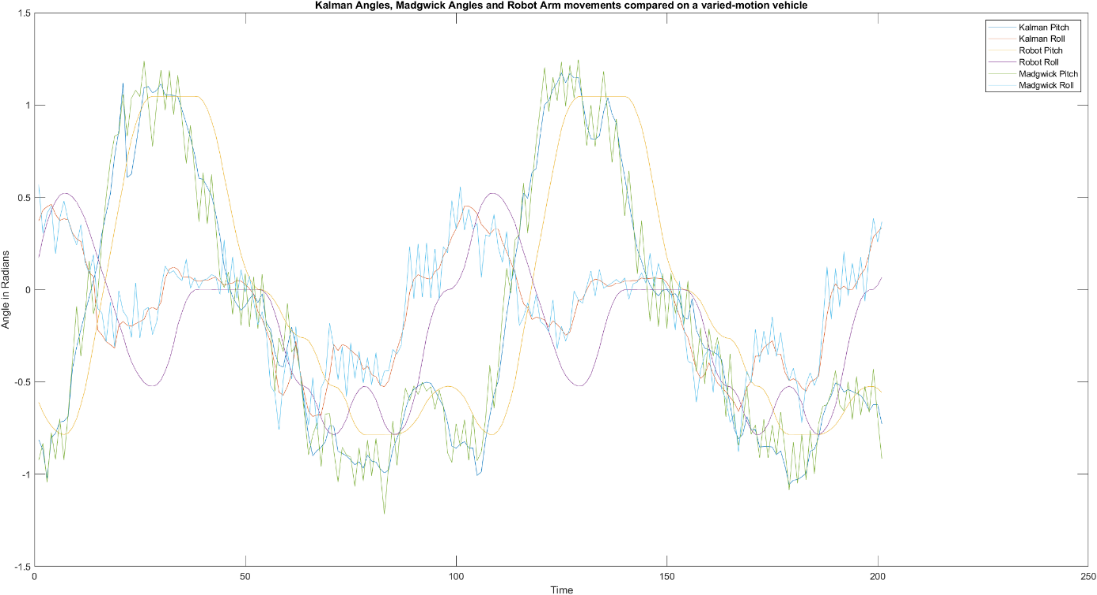


Figure 3.8 “Best-fit” alignment - close up of samples from 100-300.

A graph showing a variety of colored lines

Description automatically generated with medium confidence

Figure 3.9 “Best-fit” alignment - close up of samples from 1000-3000.

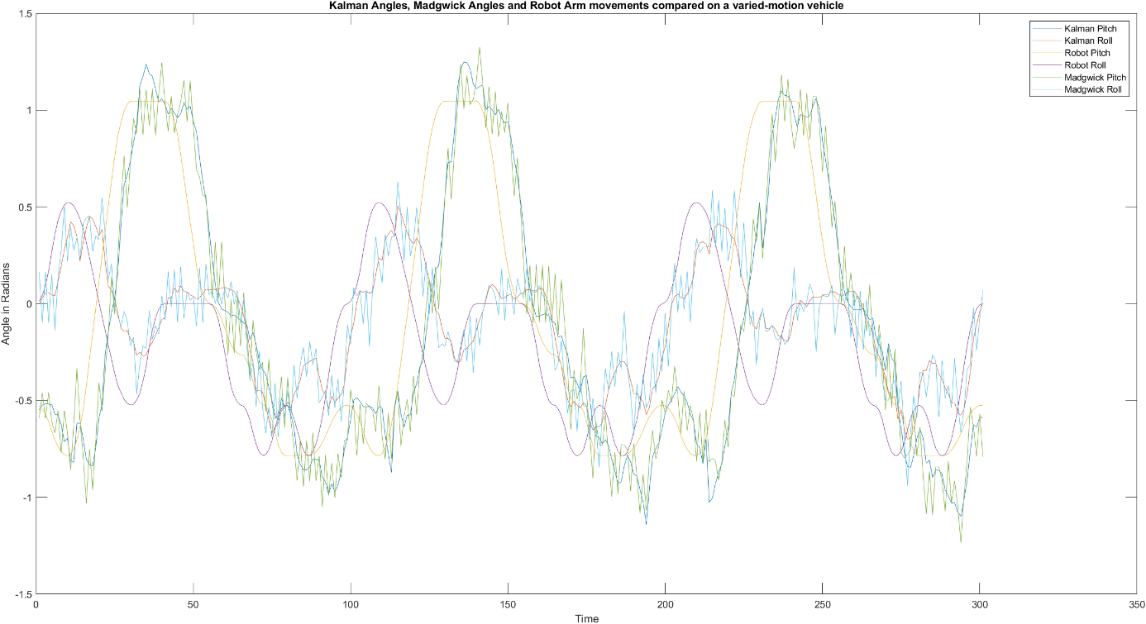


Figure 3.10 “Best-fit” alignment - close up of samples from 3000-3300.

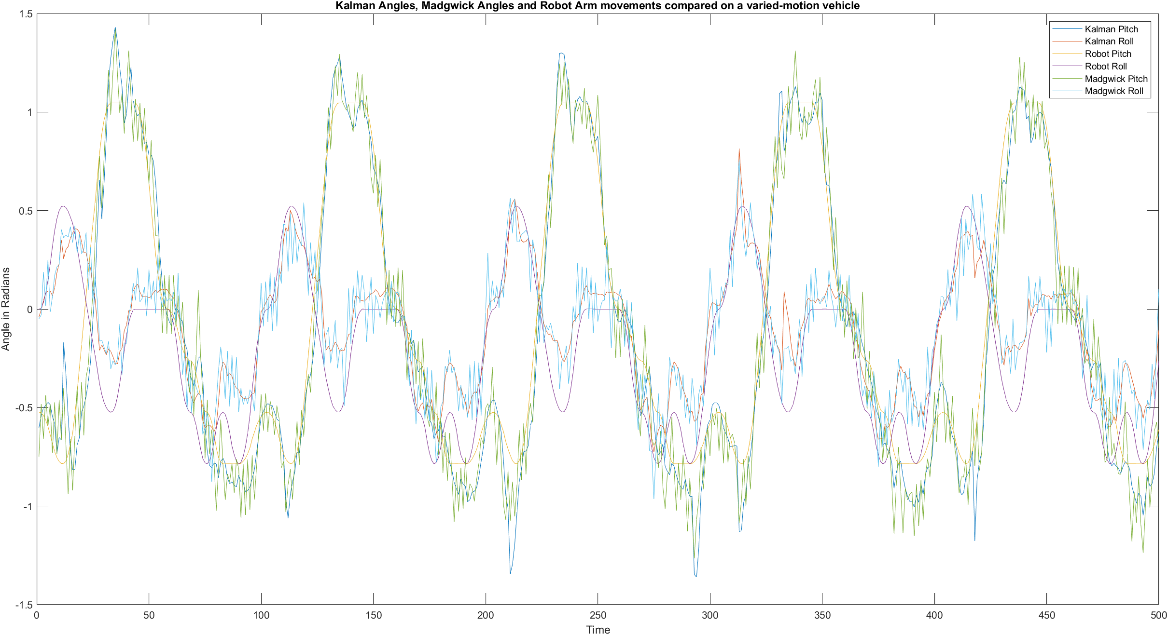


Figure 3.11 “Best-fit” alignment - close up of samples from 4500-4999.

Even with the alignment of elapsed time, rather than by the number of samples, the alignment is not perfect as can be seen in Figures 3.11 to 3.13, showing that the two devices do not always keep time in the same way. The misalignment is consistent however, as distinct from using sample alignment, and arises from using the middle IMU (Camera) as the alignment method (the initial robot arm movement may be recorded on one of the other IMUs) , as well as differences in performance between the devices.

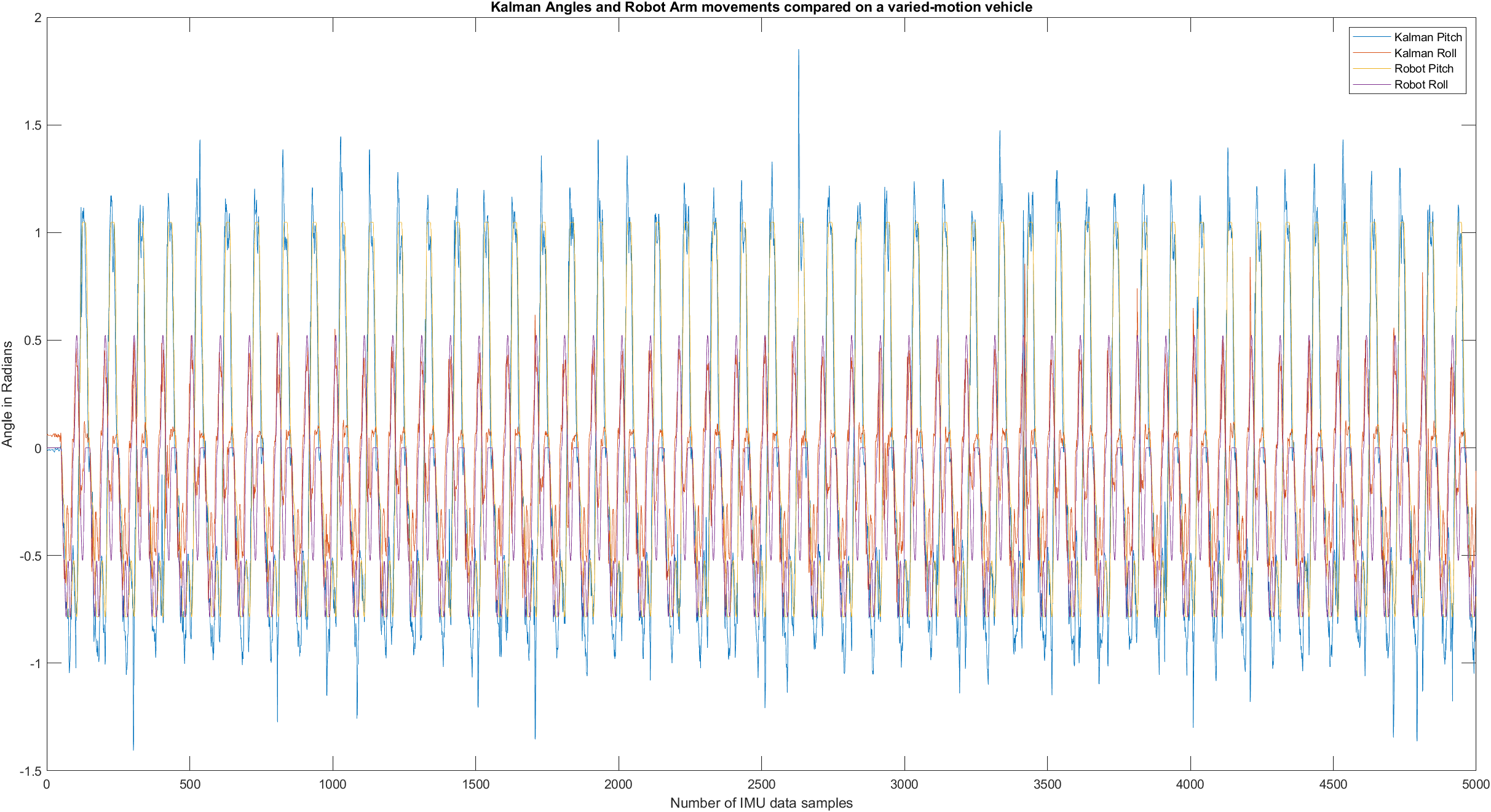


Figure 3.12 Overall alignment of IMU and robot arm

A graph with colorful lines

Description automatically generated

Figure 3.13 Alignment of IMU and robot arm from samples 1000-1999

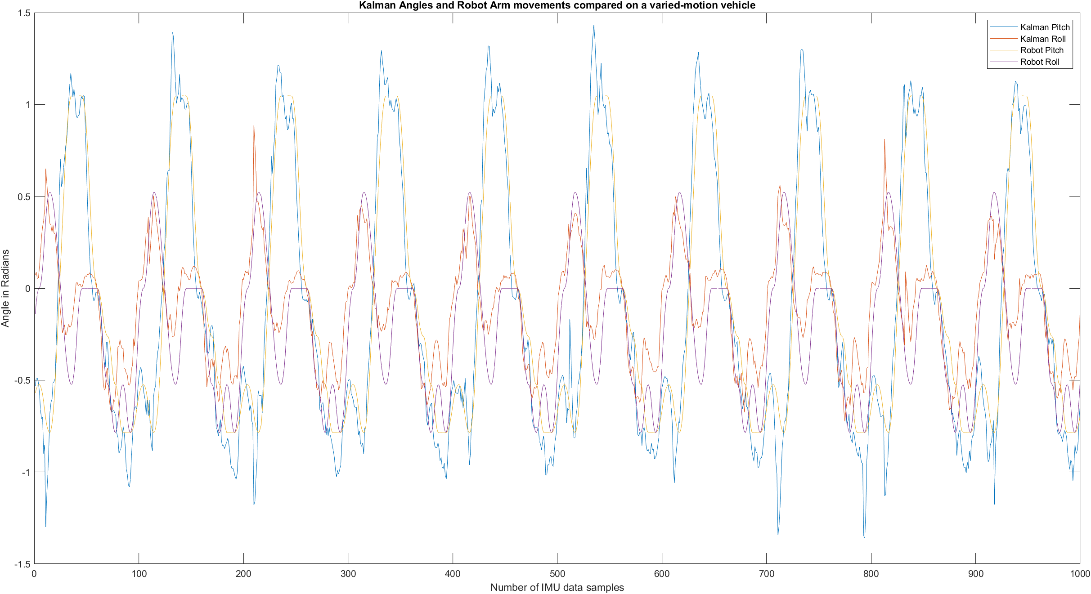


Figure 3.14 Allignment of IMU and robot arm from samples 4000-4999

A sample of the raw IMU data taken from the stationary vehicle is shown below in Table 3.1. All IMU data was captured but only the Camera IMU data is displayed in this table. The large value of the z (vertical) axis 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. Results from this initial calibration can be obtained from Appendix 2. 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. The first three lines of data are shown in Table 3.1.

Table 3.1 First three lines of data from the Camera IMU

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| 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 |

The rationale for calibration is based on the works of Qureshi et al (Qureshi & Golnaraghi, 2017)   
but utilised a set of setsquares (permitting fixed angles of 0,30,45,60 and 90 degrees) to align the IMU sensors in various angles of 90 degrees to apply appropriate offset and bias values as access to the robot arm was not available at the time.   
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 3.2 lists gyroscope offset values for the Camera IMU.

Table 3.2 Camera IMU Gyroscope Calibration offsets

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| 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 3.3 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.

Table 3.3 Camera IMU Accelerometer Slope and Offset Table

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| 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 |

The offset and scaling values from Tables 3.2 and 3.3 are applied to each IMU 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.  
  
With the robotic arm in the neutral position as shown in Figures 3.4 and 3.5, a sample of static results from the robot arm sensors is shown in Table 3.4.

Table 3.4 Sample of Euler angle results from the robt arm using tool arm sensors while at rest.

|  |  |  |
| --- | --- | --- |
| Euler Z | Euler Y | Euler X |
| 0.278238171 | 0.52853157 | -90.0214431 |

Table 3.5 Joint angles of Robot at rest

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Angle | Base | Shoulder | Elbow | Wrist 1 (Roll) | Wrist 2 (Pitch) | Wrist 3 (Yaw) |
| Radians | -0.0002993 | -1.570928 | -2.3667 e-05 | 8.39233 e-05 | 1.570547 | -7.230440248 e-05 |
| Degrees | -0.0171474 | -90.00756 | -0.001356 | 0.00480845 | 89.985754 | -0.004142737 |

In the next section, the experiment process is outlined and details of the post processing of the IMU data using the various filters and neural network models is presented.

## Experiments

In this section the experiments undertaken on the chassis are outlined and details of the post processing of the IMU data using the various filters and neural network models is presented.

Table 3.6 contains a list of the experiments based on the method process of Figure 3.2.  
The first column ties the experiment to the method process outlined in Figure 3.2. The table also contains an experiment name, which IMUs will be evaluated during the experiment, which post-processing processes will be undertaken on the data, and the names of the MATLAB processing scripts and robot movement programs required to undertake the experiment.

Tables 3.7 through 3.12 describe the robotic arm movements for each robot Movement program listed in Table 3.6.  
  
Yaw movement data will not be derived as the IMUs would realistically require magnetometer data to calculate this information and the aluminium baseboard (and steel construction of the vehicle chassis when mounted in production) would likely introduce too much variability to the measurements for a magnetometer to be useful as per the findings of Fan (Fan et al., 2017). This assumption is investigated in Experiment 6 results section using the baseboard chassis, alone.

Table 3.6 Experiments.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Purpose | Experiment Name | IMUs sampled | Process’ | Capture Name | Robot Movement Program |
| 2. Determining sensor noise | Stationary | Camera | Madgwick Kalman | Stationary | - |
| 3. Roll sensitivity | Roll | Camera | Madgwick Kalman | Roll | Roll |
| 4. Pitch sensitivity | Pitch | Camera | Madgwick Kalman | Pitch | Pitch |
| 5. Comparisons-Varied movement | Varied | Camera 3 IMUs All IMUs | Madgwick Kalman NN | Varied | Varied |
| 5. Comparisons-Untrained data for NN | Varied- NNLive | Camera 3 IMUs All IMUs | NN | Varied-NNlive | Varied-NNlive |
| 6. Is a magnetometer useful? | Magnetometer | Camera 3 IMUs All IMUs | Madgwick Kalman NN | Magnetometer | Varied |
| 7. Can complex movements be handled | Rotation | Camera 3 IMUs All IMUs | Madgwick Kalman NN | Rotation | Rotation |
| 7. Complex movements-Untrained data | Rotation- NNLive | Camera3 IMUS All IMUs | NN | Rotation- NNlive | Rotation-NNlive |
| 8. Is there a bias in the Z axis? | FL-IMU-down | All IMUs | Madgwick Kalman NN | FL-down | Varied |
| 8. Is there bias in the X and Y axes? | FL-down and Rear IMUs at 90 degrees | All IMUs | Madgwick Kalman NN | FL-down-R-rotated | Varied |
| 9. IMU mounted vertically to detect Yaw | Yaw | All IMUs | Madgwick Kalman NN | Yaw | Varied |

Table 3.7 Robot Movement Program: Roll (Steps 2 and 3 are repeated)

|  |  |  |  |
| --- | --- | --- | --- |
| Name:   Sequence Number: | IMU Angles (Rotation:Roll: Pitch) Degrees | Robot Joint Angle (Radians) (Base:Wrist1:Wrist2:Wrist3) (Rotation:Roll:Pitch:Yaw) | Robot Angles (Degrees) (Base:Wrist1:Wrist2:Wrist3) (Rotation:Roll:Pitch:Yaw) |
| 0 | 0 : 0 : 0 | 0 : 0 : π/2 : 0 | 0 : 0 : 0 : 0 |
| 1 | 0 : -π/4 : 0 | 0 : -π/4 : π/2 : 0 | 0 : -45 : 0 : 0 |
| 2 | 0 : -π/3 : 0 | 0 : -π/3 : π/2 : 0 | 0 : -60 : 0 : 0 |
| 3 | 0 : π/3 : 0 | 0 : π/3 : π/2 : 0 | 0 : 60 : 0 : 0 |

Table 3.8 Robot Movement Program: Pitch

|  |  |  |  |
| --- | --- | --- | --- |
| Name:   Sequence Number: | IMU Angles (Rotation:Roll: Pitch) | Robot Joint Angle (Radians) (Base:Wrist1:Wrist2:Wrist3) (Rotation:Roll:Pitch:Yaw) | Robot Angles (Degrees) (Base:Wrist1:Wrist2:Wrist3) (Rotation:Roll:Pitch:Yaw) |
| 0 | 0 : 0 : 0 | 0 : 0 : 0 : 0 | 0 : 0 : 0 : 0 |
| 1 | 0 : 0 : π/6 | 0 : 0 : π/6 : 0 | 0 : 0 : 30 : 0 |
| 2 | 0 : 0 : π/4 | 0 : 0 : π/4 : 0 | 0 : 0 : 45 : 0 |
| 3 | 0 : 0 : π/3 | 0 : 0 : π/3 : 0 | 0 : 0 : 60 : 0 |
| 4 | 0 : 0 : π/6 | 0 : 0 : π/6 : 0 | 0 : 0 : -30 : 0 |
| 5 | 0 : 0 : -π/4 | 0 : 0 : -π/4 : 0 | 0 : 0 : -45 : 0 |
| 6 | 0 : 0 : -π/3 | 0 : 0 : -π/3 : 0 | 0 : 0 : -60 : 0 |

Table 3.9 Robot Movement Program: Varied

|  |  |  |  |
| --- | --- | --- | --- |
| Name:   Sequence Number: | IMU Angles (Rotation:Roll: Pitch) | Robot Joint Angle (Radians) (Base:Wrist1:Wrist2:Wrist3) (Rotation:Roll:Pitch:Yaw) | Robot Angles (Degrees) (Base:Wrist1:Wrist2:Wrist3) (Rotation:Roll:Pitch:Yaw) |
| 1 | 0 : π/12 : π/3 | 0 : π/12 : π/3 : π/2 | 0 : 15 : 60 : 90 |
| 2 | 0 : π/6 : π/4 | 0 : π/6 : π/4 : π/2 | 0 : 30 : 45 : 90 |
| 3 | 0 : π/4 : π/3 | 0 : π/4 : π/3 : π/2 | 0 : 45 : 60 : 90 |
| 4 | 0 : π/4 : π/4 | 0 : π/4 : π/4 : π/2 | 0 : 45 : 45 : 90 |
| 5 | 0 : π/6 : π/2 | 0 : π/6 : π/2 : π/2 | 0 : 30: 90 : 90 |
| 6 | 0 : π/4 : 2π/3 | 0 : π/4 : 2π/3 : π/2 | 0 : 45 : 120 : 90 |
| 7 | 0 : -π/3 : π/3 | 0 : -π/3 : π/3 : π/2 | 0 : -60: 60 : 90 |
| 8 | 0 : -π/3 : π/2 | 0 : -π/3 : π/2 : π/2 | 0 : -60: 90 : 90 |

Table 3.10 Robot Movement Program: Varied-NNlive

|  |  |  |  |
| --- | --- | --- | --- |
| Name:   Sequence Number: | IMU Angles (Rotation:Roll: Pitch) | Robot Joint Angle (Radians) (Base:Wrist1:Wrist2:Wrist3) (Rotation:Roll:Pitch:Yaw) | Robot Angles (Degrees) (Base:Wrist1:Wrist2:Wrist3) (Rotation:Roll:Pitch:Yaw) |
| 0 | 0:0:π/2 | 0 : 0 : π/2 : π/2 | 0 : 0 : 90 : 90 |
| 1 | 0:π/3:π/3 | 0 : π/3 : π/3 : π/2 | 0 : 60 : 60 : 90 |
| 2 | 0:π/6:π/4 | 0 : π/6 : π/4 : π/2 | 0 : 30 : 45 : 90 |
| 3 | 0:-π/3:2π/3 | 0 : -π/3 : 2π/3 : π/2 | 0 : -60 : 120 : 90 |
| 4 | 0:π/3:2π/3 | 0 : π/3 : 2π/3 : π/2 | 0 : 60 : 120 : 90 |
| 5 | 0:π/6:π/3 | 0 : π/6 : π/3 : π/2 | 0 : 30 : 60 : 90 |
| 6 | 0:-π/12:2π/3 | 0 : -π/12 : 2π/3 : π/2 | 0 : -15 : 120 : 90 |
| 7 | 0:-3π/36:5π/9 | 0 : -13π/36 : 5π/9 : π/2 | 0 : -65 : 100 : 90 |
| 8 | 0:-5π/18:2π/3 | 0 : -5π/18 : 2π/3 : π/2 | 0 : -50 : 120 : 90 |
| 9 | 0:-5π/18:2π/9 | 0 : -5π/18 : 2π/9 : π/2 | 0 : -50 : 40 : 90 |
| 10 | 0:2π/9:2π/9 | 0 : 2π/9 : 2π/9 : π/2 | 0 : 40 : 40 : 90 |
| 11 | 0:5π/18:2π/3 | 0 : 5π/18 : 2π/3 : π/2 | 0 : 50 : 120 : 90 |

Table 3.11 Robot Movement Program - Rotation

|  |  |  |  |
| --- | --- | --- | --- |
| Name:   Sequence Number: | IMU Angles (Rotation:Roll: Pitch) | Robot Joint Angle (Radians) (Base:Wrist1:Wrist2:Wrist3) (Rotation:Roll:Pitch:Yaw) | Robot Angles (Degrees) (Base:Wrist1:Wrist2:Wrist3) (Rotation:Roll:Pitch:Yaw) |
| 0 | 0:0:0 | 0 : 0 : π/2 : π | 0 : 0 : 90 : 180 |
| 1 | π/6:π/12:7π/12 | π/6 : π/12 : 7π/12 : π | 30 : 15 : 105 : 180 |
| 2 | π/3:0:π/2 | π/3 : 0 : π/2 : π | 60 : 0 : 90 : 180 |
| 3 | π/2:-π/12:π/3 | π/2 : -π/12 : π/3 : π | 90 : -15 : 60 : 180 |
| 4 | 2π/3:0:π/2 | 2π/3 : 0 : π/2 : π | 120 : 0 : 90 : 180 |
| 5 | 5π/6:-π/12:7π/12 | 5π/6 : -π/12 : 7π/12 : π | 150 : -15 : 105 : 180 |
| 6 | π:0:π/2 | π : 0 : π/2 : π | 180 : 0 : 90 : 180 |
| 7 | 7π/6:-π/12:7π/12 | 7π/6 : -π/12 : 7π/12 : π | 210 : -15 : 105: 180 |
| 8 | 4π/3:π/12:5π/12 | 4π/3 : π/12 : 5π/12 : π | 240 : 15 : 75 : 180 |
| 9 | 3π/2:π/9:19π/36 | 3π/2 : π/9 : 19π/36 : π | 270 : 20 : 95 : 180 |
| 10 | 5π/3:-π/9:2π/3 | 5π/3 : -π/9 : 2π/3 : π | 300 : -20 : 120 : 180 |
| 11 | 11π/6:π/12:13π/36 | 11π/6 : π/12 : 13π/36 : π | 330 : 15 : 65 : 180 |

Table 3.12 Robot Movement Program – Rotation-NNlive

|  |  |  |  |
| --- | --- | --- | --- |
| Name:   Sequence Number: | IMU Angles (Rotation:Roll: Pitch) | Robot Joint Angle (Radians) (Base:Wrist1:Wrist2:Wrist3) (Rotation:Roll:Pitch:Yaw) | Robot Angles (Degrees) (Base:Wrist1:Wrist2:Wrist3) (Rotation:Roll:Pitch:Yaw) |
| 0 | 0 : 0 : 0 | 0 : 0 : π/2 : π | 0 : 0 : 90 : 180 |
| 1 | π/6:π/6:2π/3 | π/6 : π/6 : 2π/3 : π | 30 : 30 : 120 : 180 |
| 2 | π/3:0:π/2:π | π/3 : 0 : π/2 : π | 60 : 0 : 90 : 180 |
| 3 | π/2:-π/6:π/4 | π/2 : -π/6 : π/4 : π | 90 : -30 : 45 : 180 |
| 4 | 2π/3:0:π/2 | 2π/3 : 0 : π/2 : π | 120 : 0 : 90 : 180 |
| 5 | 5π/6:-π/4:2π/3 | 5π/6 : -π/4 : 2π/3 : π | 150 : -45 : 120 : 180 |
| 6 | π:0: π/2 | π : 0 : π/2 : π | 180 : 0 : 90 : 180 |
| 7 | 7π/6:-π/4:23π/36 | 7π/6 : -π/4 : 23π/36 : π | 210 : 45 : 115: 180 |
| 8 | 4π/3:π/12:5π/12 | 4π/3 : π/12 : 5π/12 : π | 240 : 15 : 75 : 180 |
| 9 | 3π/2:π/9:π/6 | 3π/2 : π/9 : π/6 : π | 270 : 20 : 30 : 180 |
| 10 | 5π/3:-π/9:2π/3 | 5π/3 : -π/9 : 2π/3 : π | 300 : -20 : 120 : 180 |
| 11 | 11π/6:π/4:π/3 | 11π/6 : π/4 : π/3 : π | 330 : 45 : 60 : 180 |

Processing of the IMU data into Euler angles is undertaken by three different main processes. These are a Madgwick Filter, a Kalman filter and a neural network. For each process, a single camera IMU is evaluated and then the front 3 IMUs and then all IMUs. Later experiments investigate the use of a magnetometer and also consider the effects of sensor alignment.

MATLAB 2023a is used for data processing and analysis, using a MATLAB implementation of the Madgwick filter provided by the author of the filter, an internal MATLAB implementation of a Kalman filter and an internal MATLAB-based neural network model. Defaults are used for all filters unless these produced noticably incorrect results, wherepon the adjustments are noted.

The Madgwick filter implementation for MATLAB is supplied by the author (Madgwick, 2009) and has two internal procedures. The first, UpdateIMU, is used for accelerometer and gyroscope data only, and the second, Update, also adds support for magnetometer data. Matlab wrapper scripts were created to call these functions.  
  
The Kalman filter   
The three different systems (Madgwick filter, Kalman filter and Neural network) are compared on speed of processing, processing CPU requirements and overall accuracy.   
  
The pseudocode for the processing steps is outlined below.

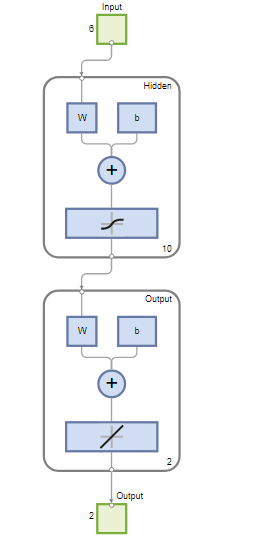
a)Read in IMU and robot arm data.  
b)Adjust for mounting angles (add or subtract the mounting angle, normally π/2)  
c)Get sampling times from robot arm data and store in a new array.  
d)Generate individual IMU arrays and set array sizes the same (sampling times will make differences) e)Using visual alignment sample locations, align robot entries with camera IMU entries.  
f)Run Madgwick and Kalman filters on data. (Magnetometer data requires different function calls)  
g)Calculate average Euler angles from 3 IMUs and all IMUs across all Euler angles.  
h)Create Prediction arrays for neural network for camera IMU, 3 IMUs and all IMUs  
i)Create Response array from robot data.  
j)Plot output.  
  
Neural network processing is left as a manual process.  
  
The initial neural network utilised for each experiment is a MATLAB 10-layer neural network with each individual axis measurement treated as an input to the neural network as shown in Figure 3.14. (Six to nine inputs for a single IMU). Outputs of the neural network shall be two - pitch and roll. Training will use the Levenberg-Marquardt (LVM) method. (Bayesian and scaled conjugate training methods were also initially evaluated but these did not offer any significant gains compared to the LVM method). The hidden layers shall use sigmoid functions and the output layer will use a linear function. By default, the system will use a random division of data into training, validation and testing sets of 70%, 15% and 15%, respectively. Different neural network topologies may need to be considered during the results section to increase accuracy.  
 

Figure 3.14 Initial Neural Network Model

After initial training, different numbers of layers and/or different process functions may be implemented to obtain better performance. Once the best neural network model is determined, a live set of robot movements shall be performed to validate the NN model on untrained data.  
  
In this chapter, the experimental method is outlined, consisting of a baseboard containing 5 IMUs which undergo movement induced by a robotic arm. Data from a single camera IMU is processed by Madgwick, Kalman filters and, intially, a 10-layer Sigmoid/Linear neural network to determine Euler angles. Different neural networks may be implemented to obtain better performance.  
Data from the front three and then all five IMUs is processed by the same three algorithms and compared against the single IMU results. Additional experiments investigate the use of a magnetometer and the alignment of IMUs. Experiment details are outlined in Tables 3.6 to 3.12.  
  
In Chapter 4, the results from these experiments are detailed and discussed, with analysis of these in Chapter 5 and conclusions reached in Chapter 6.

# Results

## Filter Performance on a stationary vehicle

Applying the MATLAB Madgwick function using the UpdateIMU procedure produced the following results on a stationary vehicle, demonstrated in Table 4.1. 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 from the camera IMU was 0.0427 seconds using the tic/toc method in MATLAB. As the code runs faster than the recommended minimum of 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 of all runs. The results of the Madgwick filter are shown in Table 4.1.

Table 4.1 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 4.1.

A graph on a white background

Description automatically generated

Figure 4.1 Madgwick filter results on stationary vehicle (Brown=Roll,Yellow=Pitch,Blue=Yaw)

The Yaw value shown in Figure 4.1 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.

The default MATLAB imufilter filter was used to represent an error-state Kalman filter for non-magnetometer data or the MATLAB ahrsfilter when magnetometer data is included. Settings are configured in the appropriate filter functions included in the github repository. These properties were configured from experimentation with the datasets to obtain the best results, matched to the robot arm data.   
  
Running the imufilter Kalman filter on the 996 sensor readings took 0.7581 seconds and produced an array of Euler angles after the conversion. Figure 4.2 shows the results and indicates that the Kalman filter also can’t handle yaw values (blue line) without magnetometer input. As mentioned above, yaw values are not handled well by filters as, without magnetometer data, there is no fixed reference point to provide accurate values. Figure 4.3 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 Kalman filter processing time is considerably longer than the Madgwick filter processing time (0.7581 vs 0.0427 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.

The robot arm was not sampled for this experiment as expected values are somewhat obvious.  
It was not believed necessary to employ a Neural Network model on a stationary vehicle as the purpose of this experiment was to obtain noise floor data from the IMU.

## Filter performance on a rolling vehicle.

The robot arm was rotated according to the appropriate angles in Table 3.7 and the Robot arm data was 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 the camera IMU data with standard settings of a sample period of 1/1001 and a default beta gain value of 0.1 and took 0.0417 seconds to run.  
The results were clearly incorrect as can be shown on Figure 4.4 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 4.5 through to 4.7.

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Figure 4.4 Madgwick results from a stationary vehicle with a default gain of 0.1

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Figure 4.5 Madgwick Filter on a rolling vehicle with a gain of 1

Using a gain of 10, the Madgwick filter took 0.0440 seconds but produced better results as can be seen in Figure 4.6.  
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Figure 4.6 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 4.7. This clearly indicates that the gyroscope output is either noisy and/or has significant drift. From looking at the data, and from examining the output of the gyroscope when the vehicle is stationary, the amount of noise is significant. This operation took 0.04997 seconds for the camera IMU. The average elapsed time for all IMUs was 0.046592 with a median of 0.04319 and max and min values of 0.06516 and 0.03855, respectively. The results from Figure 4.7 show a maximum measured value of .9948 radians instead of the expected ±π/3 (1.047) radians and the π/4 (0.7854) radian position was calculated as 0.7487 radians. If the 0.0201 radian maximum tool angle error plus the IMU’s own 1.5% inaccuracy values are combined, then this error is within the operating conditions of the sensors.

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Figure 4.7 Madgwick filter on a rolling vehicle with a gain of 15

The imufilter Kalman filter was then used to generate Euler angles. The filter operation took 0.6516 seconds for the camera IMU and produced the output shown in Figure 4.8. The average elapsed time for all IMUs was 0.3772 with a median of 0.3051 and max and min values of 0.6516 and 0.2905, respectively, taking 8.0958 times longer than the Madgwick filter. 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 desired π/3 (1.0472) angle is 1.0297 which is well within specifications of the sensors and tracks better than the 0.9948 reading of the Madgwick result. It is interesting to see the various phasing differences between the values. This is most likely because of the different timings of the robot arm versus timing of how the different IMU units are polled.   
The multiplexer switching time was measured as taking an average of 515 nanoseconds at the start of the movement set down to 41 nanoseconds after 30 seconds of operation. After 1 minute of operation, the multiplexing switching time was measured at 47 milliseconds. The time taken to read acceleration data is 2202 milliseconds and the time taken to read gyroscope data is 1659 milliseconds. Total time taken to measure each IMU was 2400 milliseconds. Between each measurement the script takes 71 milliseconds (excluding multiplexor switching time) to begin the processing of the next set of measurements. The robot arm is sampled at approximately 6403 readings per second which equates to a time of 0.15625 milliseconds per reading.

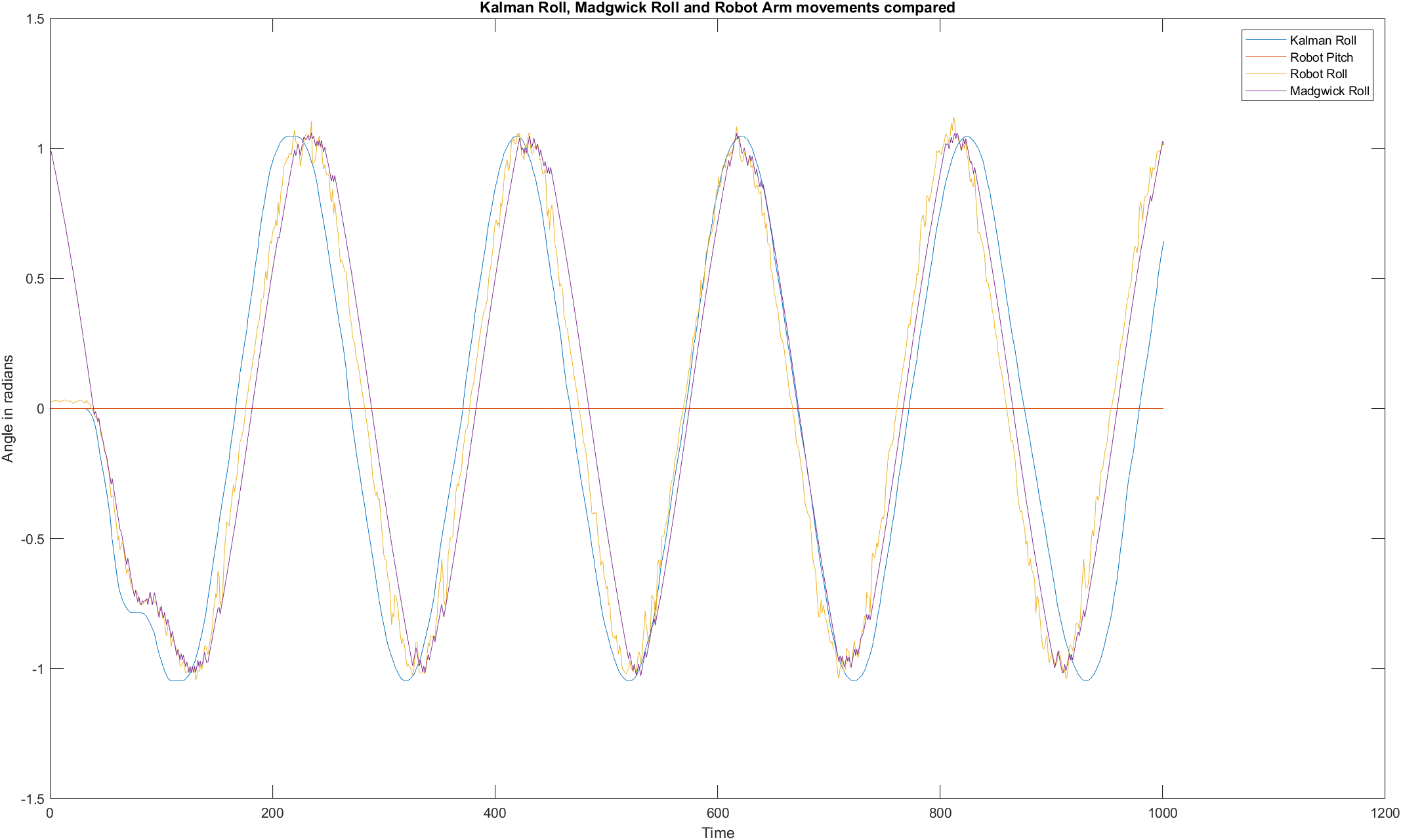


Figure 4.8 Filter and Robot arm data for a rolling vehicle using Camera IMU values.

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Figure 4.9 Averages of Filter Roll values against robot arm movements

Plotting the mean of the Madgwick IMU values and the mean of the Kalman IMU values against the robot arm movements shows that both phasing and amplitude change as seen in Figure 4.9. This indicates that, as somewhat expected, using different IMUs for alignment against the robot arm will change the phasing discrepancies and using an average of the data significantly decreases peak amplitude in both positive and negative peak values, indicating a wide spread of values obtained from the various IMUs. In terms of tracking the robot arm movements, both the Kalman and the Madgwick filters make good attempts and there is little between the filter results to merit the use of the more computationally expensive Kalman filter. The main likely explanation for the difference in phasing is that alignment of the robot arm is on first movement, which may not coincide with the sampling of the camera IMU value, however, the performance differences of the two computers will also play a small part in timing differences.

It was not deemed necessary to configure a Neural Network to analyse a simple rolling movement.

## Filter performance on a pitching vehicle

The robot arm was rotated according to the appropriate angles in Table 3.1 associated with the pitch test. The Robot arm data was synchronised with the IMU data via manual alignment. The single camera IMU data produced 995 readings in the 120 second period.

Applying the Madgwick filter with a beta of 15 on the gathered camera IMU data took an average of 0.04758 seconds. The average elapsed time for all IMUs was 0.0432 with a median of 0.0431 and max and min values of 0.04758 and 0.0401, respectively.  
The Kalman filter took 0. 4268 seconds on the same data. The average elapsed time for all IMUs was 0.3271 with a median of 0.2991 and max and min values of 0.4268 and 0.2897, respectively.  
Using the average values, the Kalman filter took 7.568 times longer than the Madgwick filter to process the pitch values.   
Figure 4.10 shows the results of the filters compared to the robot arm data.  
A graph showing a graph

Description automatically generated with medium confidence

Figure 4.10 Filter and robot arm data for a pitching vehicle using camera IMU values

Figure 4.11 shows the mean of Madgwick and Kalman results from all IMUs against the robot arm data.

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Figure 4.11 Averages of Filter Roll values against pitching robot arm movements

Averaging the values over all IMU pitch results produced errors in amplitude and phase, concentrating at zero crossing points, as seen in Figure 4.11. The Madgwick filter in particular shows some considerable oscillation around the zero crossing points when averaged that did not appear when using the single camera IMU. The Kalman filter faltered at an average of -0.655 radians while the Madgwick filter oscillated between this value and between +0.589 and +0.606.  
These results indicate there are some significant data discrepancies between the IMU units and/or variations in the input data between the IMUs.

It was not deemed necessary to configure a Neural Network for a simple pitching movement.

## Filter Performance on a varied roll and pitch vehicle

The robot arm was rotated according to the appropriate angles relating to the varied movement test outlined in Table 3.1. The Robot arm data was synchronised with the IMU data via manual alignment. The single camera IMU data produced 4998 readings in the 599.5 second period.

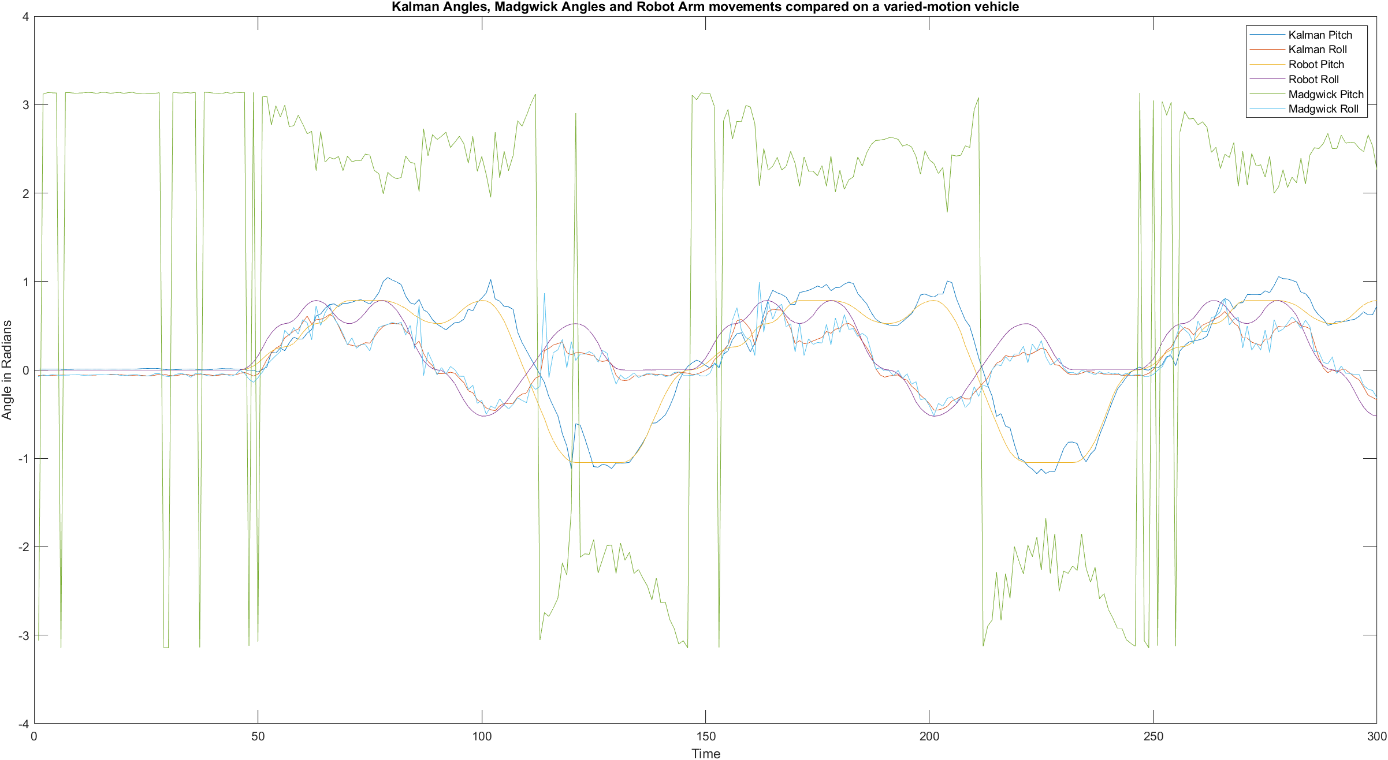
The Madgwick filter was applied to this data with standard settings of a Sample Period of 1/8.3333 and a default beta gain value of 15 and took an average of 0.2626 seconds to run. The average elapsed time for all IMUs was 0.2610 with a median of 0.2626 and max and min values of 0.2675 and 0.2532, respectively. Figure 4.12 shows these results, along with the Kalman results discussed below.  
  
The Kalman filter previously used was applied to the data and the output is also presented in Figure 4.12.  


Figure 4.12 Filter and robot arm varied-motion data using a Madgwick sample rate of 8.33

The results shown in Figure 4.12 indicate that the Kalman filter adequately tracks the robot arm movement, as does the Madgwick roll component, but using the actual sample rate as the sampling rate in the Madgwick filter is clearly producing nonsensical results. In Figure 4.13, a sampling rate of the size of the sampled data (4998 samples in this case) is selected, which is also clearly not sensible.

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Figure 4.13 Filter and robot arm varied-motion data using a Madgwick sample rate of 4998.

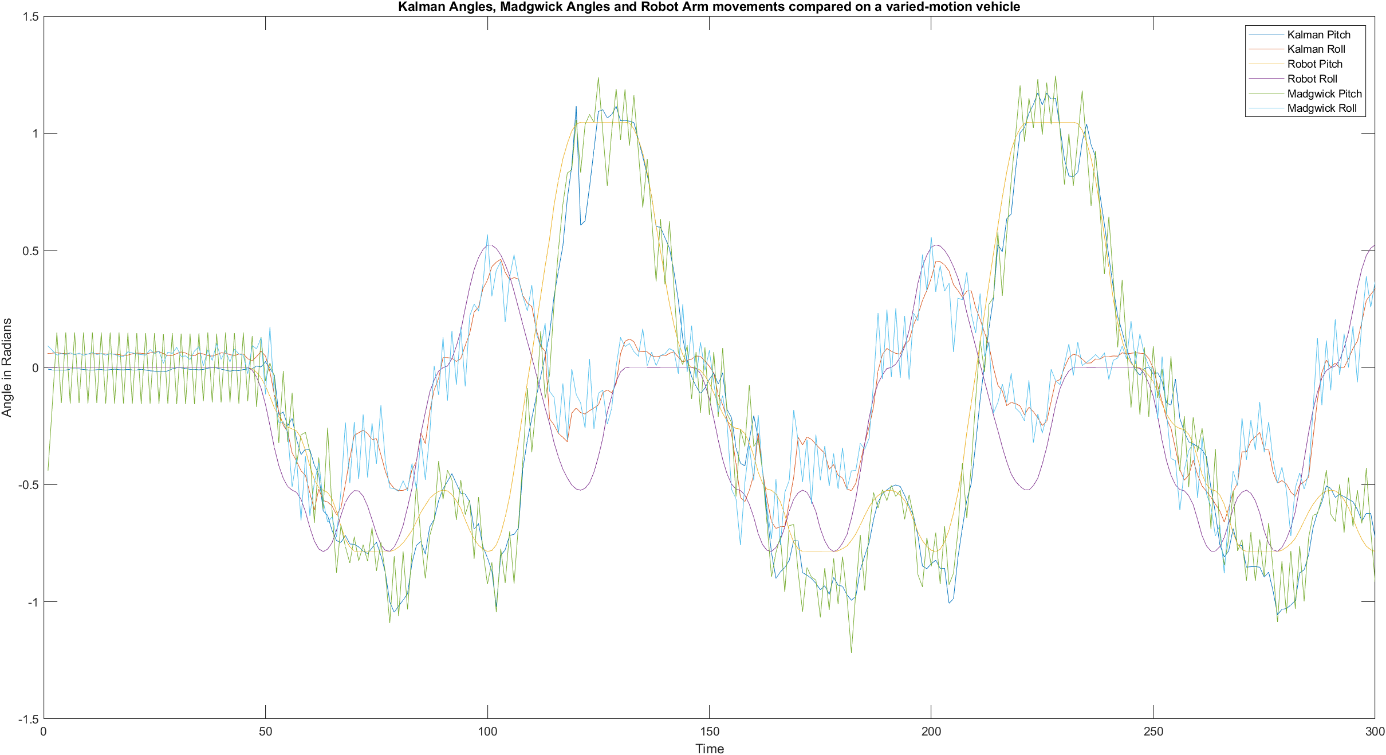
Since the Madgwick filter operates by integrating past data, it was surmised that setting the sample rate to the number of time periods used to describe a complete movement set would be ideal. For this set of movement data, the period is approximately 100. Utilising this value in the Madgwick filter parameters produced a better result as can be seen in Figure 4.14 but does indicate the importance of setting the correct sampling rate. Too short and the descent algorithm overfits and too long and the descent algorithm underfits.   


Figure 4.14 Madgwick and Kalman values with a sample rate of 100

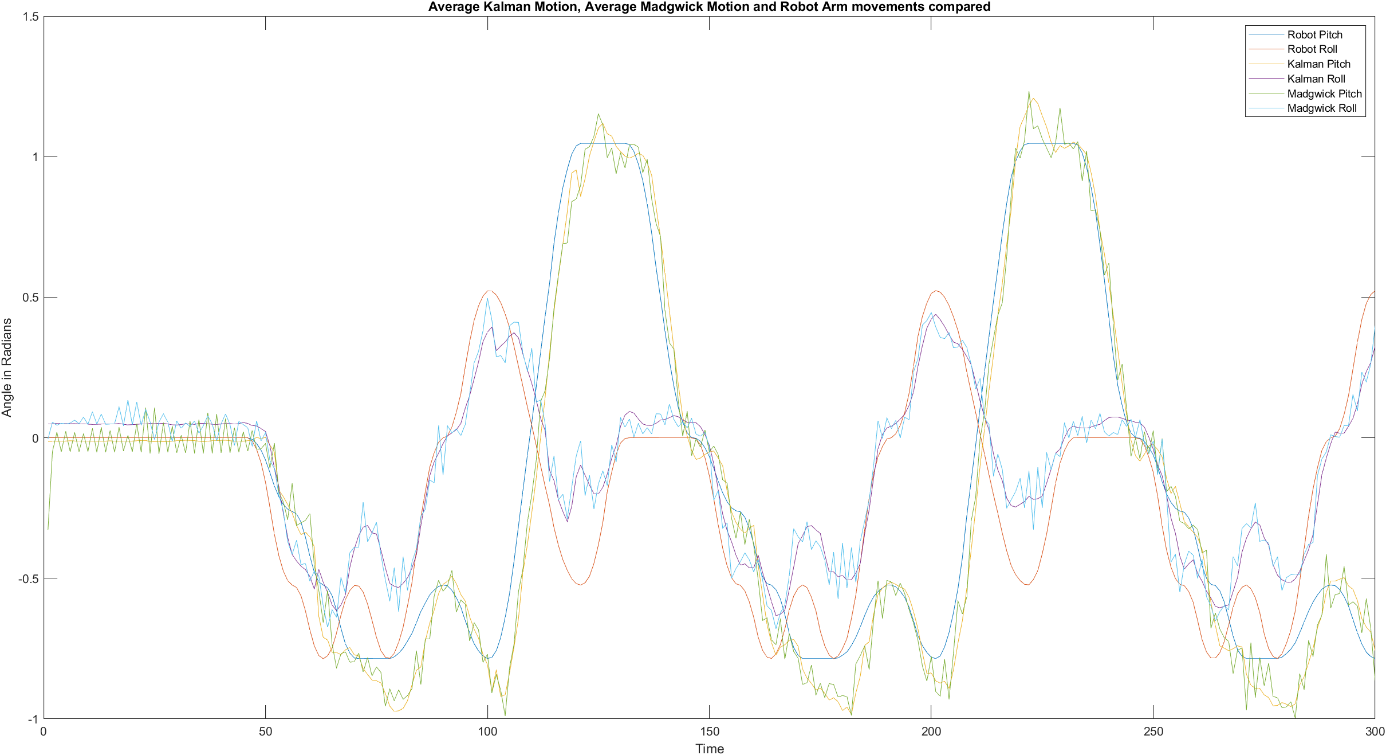
Averaging the IMU results reduces the noise somewhat as shown in Figure 4.15.  


Figure 4.15 Averages of Madgwick and Kalman values with a sample rate of 100

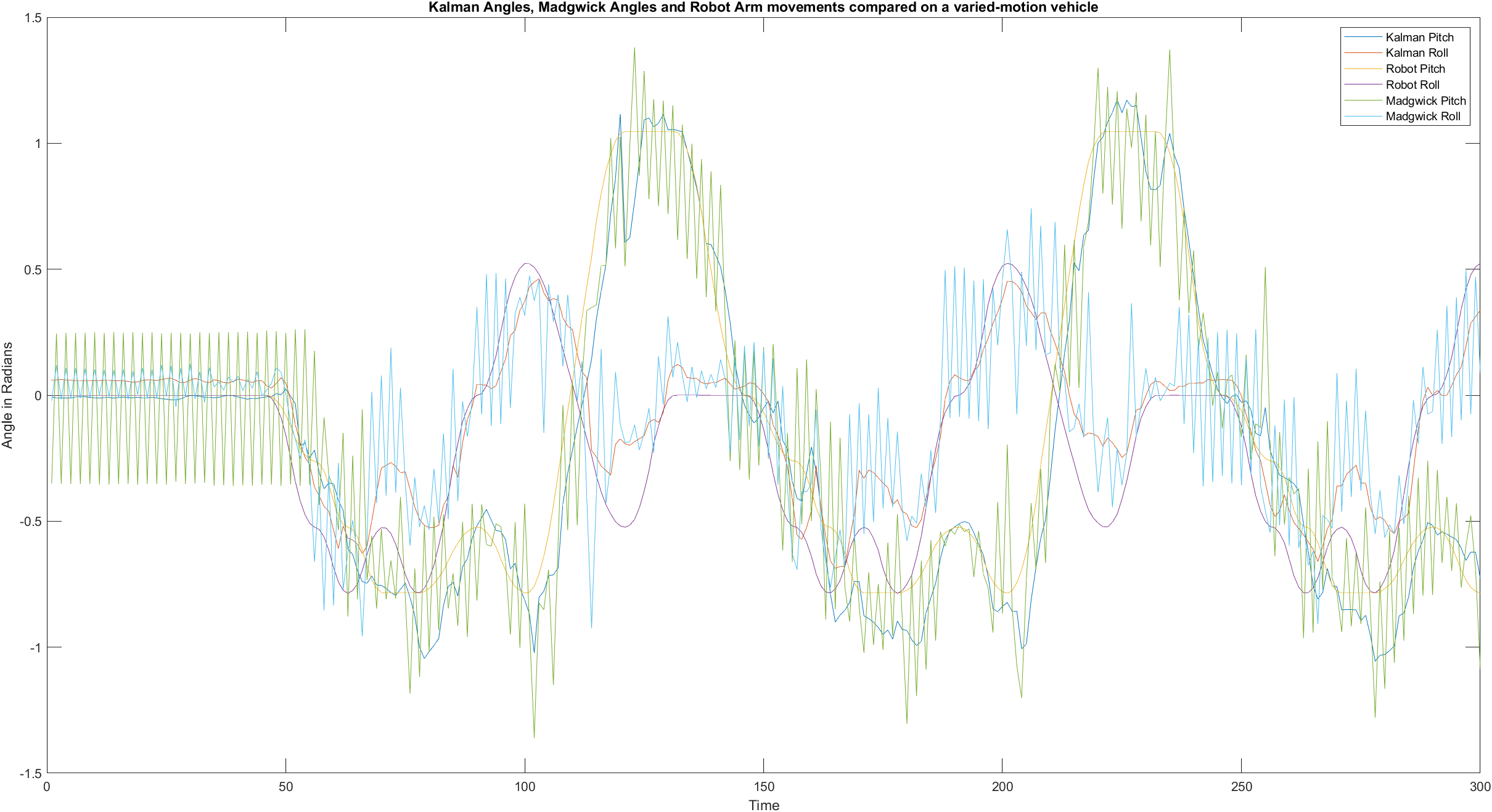
Experimenting with different sample rate values (Figure 4.16 and 4.17 show two examples of this experimentation) indicated that the best fit was the surmised opinion that the sample rate should contain a set of samples that describe a group of movements. Over a long period of time the Madgwick method will become increasingly inaccurate without a form of reset. In production, this will prove difficult to implement reliably and will likely need to be adjusted based on topology. Averaging the results across IMUs reduces noise which both tidies up output and partially mitigates the issue, but the problem remains when sampling over a long period.

Figure 4.16 Madgwick and Kalman values with a sample rate of 50

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Figure 4.17 Madgwick and Kalman values with a sample rate of 500

The interplay between sample rate and beta value was explored in Figures 4.18 and 4.19. The sample rate was left at 100 and the beta value was altered down from 15 to the configured default of 0.5 (Figure 4.18), and to 1/3 of the previously determined value of 15, which is 5.0 (Figure 4.19).

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Figure 4.18 Madgwick filter beta value set to 0.5 with a sample rate of 100

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Figure 4.19 Madgwick filter beta value set to 5.0 with a sample rate of 100

<TBC> Talk about interplay

## Neural network using a single IMU.

Feeding the measured gyroscope and accelerometer data from the camera IMU into the initial design of the neural network, and taking all network defaults, the network was trained, and the results obtained are shown in Figures 4.20 to 4.24 and Tables 4.2 and 4.3.

Table 4.2 Neural Network training results on a varied-motion vehicle.

|  |  |  |  |
| --- | --- | --- | --- |
|  | Observations | MSE | R |
| Training | 3499 | 0.0441 | 0.9219 |
| Validation | 750 | 0.0421 | 0.9250 |
| Test | 750 | 0.0423 | 0.9241 |

Table 4.3 Initial Neural Network training results with default layer size of 10

|  |  |  |  |
| --- | --- | --- | --- |
| Unit | Initial Value | Stopped Value | Target Value |
| Epoch | 0 | 19 | 1000 |
| Elapsed Time | - | 00:00:01 | - |
| Performance | 1.28 | 0.0438 | 0 |
| Gradient | 2.62 | 0.00683 | 1e-07 |
| Mu | 0.001 | 1e-05 | 1e+10 |
| Validation Checks | 0 | 6 | 6 |

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Figure 4.20 Initial Neural Network Performance plot with default layer size of 10

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Figure 4.21 Initial Neural Network Error Histogram plot with default layer size of 10

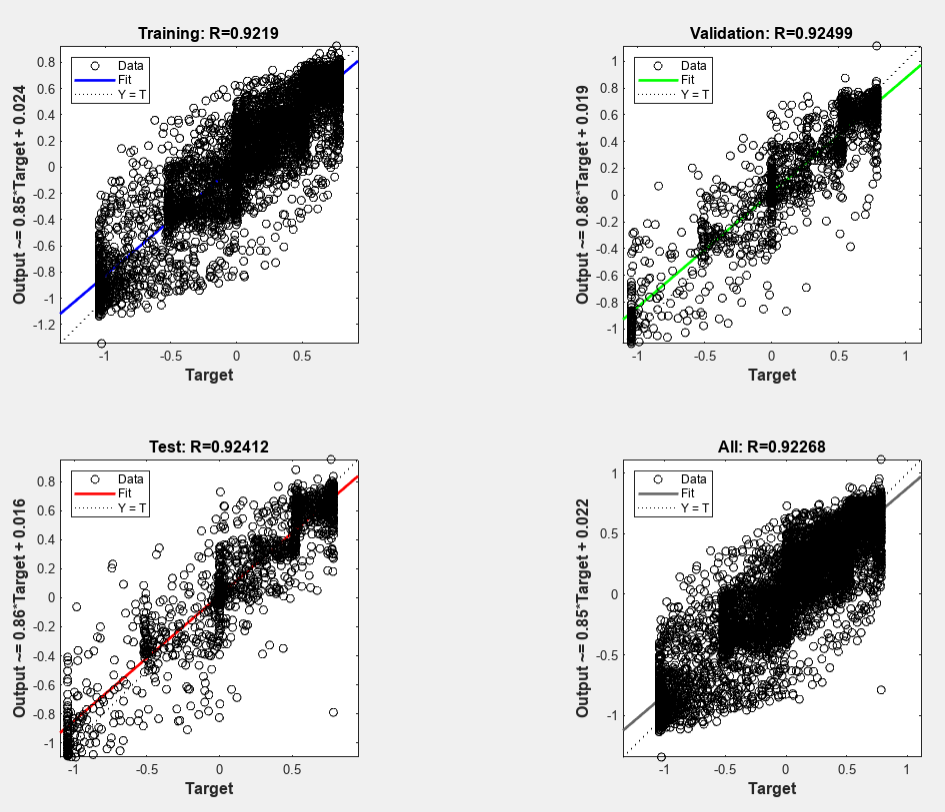


Figure 4.22 Initial Neural Network Regression plots with default layer size of 10

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Figure 4.23 Initial Neural Network traiing state plot with 10 layers

The initial neural network selected by nnstart has 10 hidden sigmoid layers. Doubling the number of layers from 10 to 20 produced the results shown in Tables 4.4 and 4.5 and Figures 4.25 to 4.27.

Table 4.4 Training results of initial neural network with a layer size of 20.

|  |  |  |  |
| --- | --- | --- | --- |
| Unit | Initial Value | Stopped Value | Target Value |
| Epoch | 0 | 25 | 1000 |
| Elapsed Time | - | 00:00:00 | - |
| Performance | 1.57 | 0.0411 | 0 |
| Gradient | 2.74 | 0.00262 | 1e-07 |
| Mu | 0.001 | 1e-05 | 1e+10 |
| Validation Checks | 0 | 6 | 6 |

Table 4.5 Training Results of initial neural network with a layer size of 20.

|  |  |  |  |
| --- | --- | --- | --- |
|  | Observations | MSE | R |
| Training | 3499 | 0.0414 | 0.9267 |
| Validation | 750 | 0.0419 | 0.9255 |
| Test | 750 | 0.0455 | 0.9193 |

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Figure 4.24 Initial Neural Network Performance plot with 20 layers

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Description automatically generated with medium confidence

Figure 4.25 Initial Neural Network Error Histogram plot with 20 layers

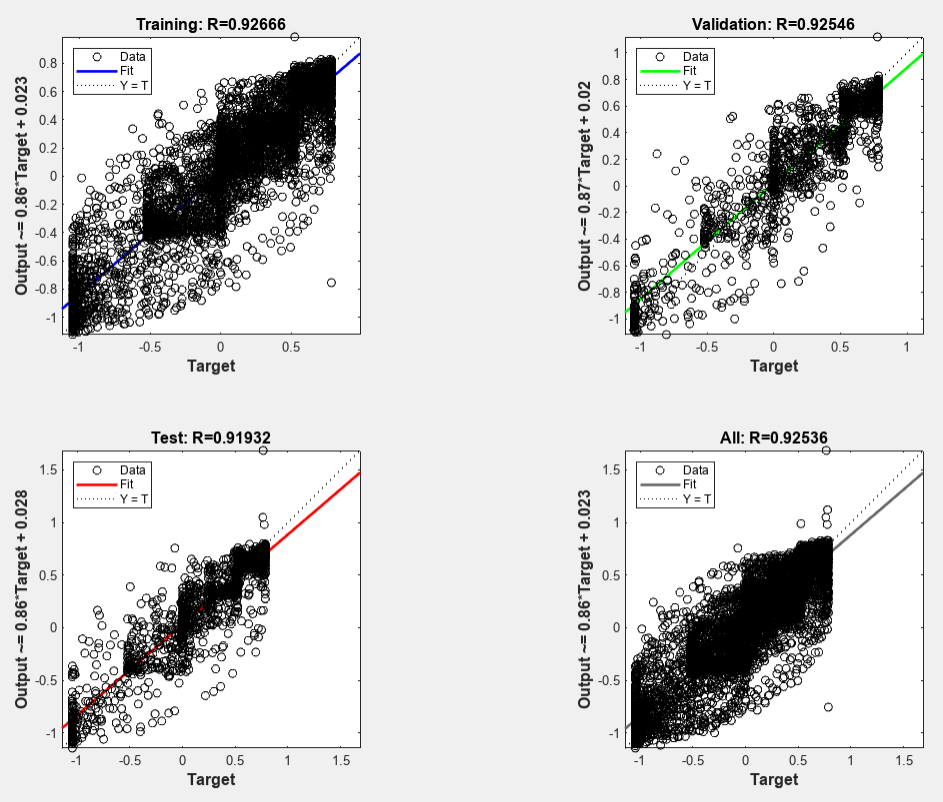


Figure 4.26 Initial Neural Network Regression plot with 20 layers

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Figure 4.27 Initial Neural Network Training State plot with 20 layers

The regression plots of Figure 4.26 show the fitting line in the middle of a pleasing random balance of data points on either side, indicating that the fit line is a good representation of the dataset. This good fit result occurs despite the presence of some outlying data values.

Dropping the number of layers down to 5 gave the training results shown in Tables 4.6 and 4.7. These are good results and only slightly less performant than the 10-layer model, showing that this problem is a relatively simple problem for a neural network to solve.

Table 4.6 Training progress on a 5 layer Neural network using the Camera IMU

|  |  |  |  |
| --- | --- | --- | --- |
| Unit | Initial Value | Stopped Value | Target Value |
| Epoch | 0 | 15 | 1000 |
| Elapsed Time | - | 00:00:00 | - |
| Performance | 0.472 | 0.0454 | 0 |
| Gradient | 0.653 | 0.0162 | 1e-07 |
| Mu | 0.001 | 1e-06 | 1e+10 |
| Validation Checks | 0 | 6 | 6 |

Table 4.7 Training results on a 5-layer Neural Network

|  |  |  |  |
| --- | --- | --- | --- |
|  | Observations | MSE | R |
| Training | 3499 | 0.0459 | 0.9186 |
| Validation | 750 | 0.0438 | 0.9217 |
| Test | 750 | 0.0452 | 0.9190 |

Table 4.8 Training results on a 3-layer Neural Network

|  |  |  |  |
| --- | --- | --- | --- |
|  | Observations | MSE | R |
| Training | 3499 | 0.0458 | 0.9191 |
| Validation | 750 | 0.0485 | 0.9118 |
| Test | 750 | 0.0506 | 0.9093 |

Table 4.9 Training results on a 2-layer Neural Network

|  |  |  |  |
| --- | --- | --- | --- |
|  | Observations | MSE | R |
| Training | 3499 | 0.0478 | 0.9146 |
| Validation | 750 | 0.0473 | 0.9195 |
| Test | 750 | 0.0515 | 0.9041 |

Table 4.10 Training results on a 1-layer Neural Network

|  |  |  |  |
| --- | --- | --- | --- |
|  | Observations | MSE | R |
| Training | 3499 | 0.0962 | 0.8172 |
| Validation | 750 | 0.0967 | 0.8161 |
| Test | 750 | 0.0930 | 0.8377 |

As seen in Tables 4.8 through 4.10, the test R values did not significantly drop (from 0.9041 at 2 layers to 0.8377 at 1 layer) until the number of layers was lowered to 1 although the testing phase showed an increase in MSE errors (0.0506 with 3 layers from 0.423 at 10 layers) when the number of layers was reduced to 2. This indicates that the data matching element of the problem is relatively simple for the model but that understanding the data relationships requires at least 2 layers. This finding matches the theorem of universal approximators proposed by Hornik (Hornik et al., 1989) that any multi-layer perceptron network of a depth of at least 1 for simple problems and a depth of 3 for more difficult problems can perform as a universal approximator.

### Filter and Neural network performance with three IMUs

Using the inputs of all three front IMUs, the 10-layer neural network above trained with the Levenberg-Marquardt method performed as outlined in Tables 4.11 and 4.12.

Table 4.11 LM Training progress on 3 IMUs with 5-layer NN

|  |  |  |  |
| --- | --- | --- | --- |
| Unit | Initial Value | Stopped Value | Target Value |
| Epoch | 0 | 17 | 1000 |
| Elapsed Time | - | 00:00:00 | - |
| Performance | 2.69 | 0.0425 | 0 |
| Gradient | 3.99 | 0.00133 | 1e -07 |
| Mu | 0.001 | 1e-05 | 1e+10 |
| Validation Checks | 0 | 6 | 6 |

Table 4.12 LM Training results on 3 IMUs with 5-layer NN

|  |  |  |  |
| --- | --- | --- | --- |
|  | Observations | MSE | R |
| Training | 3499 | 0.0428 | 0.9243 |
| Validation | 750 | 0.0453 | 0.9176 |
| Test | 750 | 0.0443 | 0.9222 |

Increasing the layers to 10 produced the tabulated outcomes shown in Figures 4.13 and 4.14.

Table 4.13 LM Training progress on 3 IMUs with 10-layer NN

|  |  |  |  |
| --- | --- | --- | --- |
| Unit | Initial Value | Stopped Value | Target Value |
| Epoch | 0 | 12 | 1000 |
| Elapsed Time | - | 00:00:00 | - |
| Performance | 1.15 | 0.0403 | 0 |
| Gradient | 2.29 | 0.00765 | 1e -07 |
| Mu | 0.001 | 1e-06 | 1e+10 |
| Validation Checks | 0 | 6 | 6 |

Table 4.14 LM Training results on 3 IMUs with 10-layer NN

|  |  |  |  |
| --- | --- | --- | --- |
|  | Observations | MSE | R |
| Training | 3499 | 0.0415 | 0.9261 |
| Validation | 750 | 0.0422 | 0.9252 |
| Test | 750 | 0.0448 | 0.9217 |

### Neural network of a varied-motion vehicle: All IMUs

Results from training with the Levenberg-Marquardt training method on a 10-layer NN with 5 IMU inputs are shown in Tables 4.15 and 4.16. MATLAB used 13.6% of CPU time and 242Mb of RAM during the process.

Table 4.15 LM Training progress on 5 IMUs with 10-layer NN

|  |  |  |  |
| --- | --- | --- | --- |
| Unit | Initial Value | Stopped Value | Target Value |
| Epoch | 0 | 12 | 1000 |
| Elapsed Time | - | 00:00:00 | - |
| Performance | 1.09 | 0.0387 | 0 |
| Gradient | 2.46 | 0.00767 | 1e-07 |
| Mu | 0.001 | 1e-05 | 1e+10 |
| Validation Checks | 0 | 6 | 6 |

Table 4.16 LM Training results on 5 IMUs with 10-layer NN

|  |  |  |  |
| --- | --- | --- | --- |
|  | Observations | MSE | R |
| Training | 3499 | 0.0407 | 0.9280 |
| Validation | 750 | 0.0402 | 0.9299 |
| Test | 750 | 0.0456 | 0.9186 |

Table 4.17 LM Training progress on 5 IMUs with 5-layer NN

|  |  |  |  |
| --- | --- | --- | --- |
| Unit | Initial Value | Stopped Value | Target Value |
| Epoch | 0 | 15 | 1000 |
| Elapsed Time | - | 00:00:00 | - |
| Performance | 0.698 | 0.0385 | 0 |
| Gradient | 1.53 | 0.00672 | 1e-07 |
| Mu | 0.001 | 1e-06 | 1e+10 |
| Validation Checks | 0 | 6 | 6 |

Table 4.18 LM Training results on 5 IMUs with 5-layer NN

|  |  |  |  |
| --- | --- | --- | --- |
|  | Observations | MSE | R |
| Training | 3499 | 0.0391 | 0.9303 |
| Validation | 750 | 0.0517 | 0.9099 |
| Test | 750 | 0.0424 | 0.9253 |

Utilising the extra IMUs (Tables 4.17 and 4.18) appears to offer no significant benefit over utilising a single IMU. The number of layers within the neural network has more effect than the number of IMUs.

### Would using a magnetometer assist accuracy?

It has been assumed that using a magnetometer would not be beneficial because of the ferrous surroundings when mounted on a vehicle. When using a robot arm, the aluminium ferrous components (including the baseboard itself) are paramagnetic in that they magnetise in the presence of a magnetic field but will not generate such a field. Using the MATLAB\_commands-Varied-mag.txt commands, magnetometer readings were utilised as well as gyroscope and accelerometer data. After synchronisation, the experiment produced the following results, plotted in Figure 4.28. The results are similar to the non-magnetometer-assisted information, confirming that the use of a magnetometer near any form of ferrous equipment (even the paramagnetic aluminium baseboard and robot arm) is of no additional benefit compared to measurements made without magnetometer information. The magnetometer was only calibrated using the internal calibration system of the IMU, so some improvements could be possible, but the results are like the calibrated errors already compensated for in the gyroscope and accelerometer readings.

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Description automatically generated

Figure 4.28 Kalman and Madgwick angles (with Magnetometer) against robot arm angles

Training a 10-layer neural network on magnetometer-assisted data produced the results described in Tables 4.19 and Figures 4.20.

Table 4.19 Training results of 10-layer Neural Network with magnetometer-assisted data

|  |  |  |  |
| --- | --- | --- | --- |
|  | Observations | MSE | R |
| Training | 4604 | 0.0172 | 0.2773 |
| Validation | 987 | 0.0161 | 0.2020 |
| Test | 987 | 0.0176 | 0.2070 |

Table 4.20 Training Progress of a 10-layer neural network with magnetometer-assisted data

|  |  |  |  |
| --- | --- | --- | --- |
| Unit | Initial Value | Stopped Value | Target Value |
| Epoch | 0 | 13 | 1000 |
| Elapsed Time | - | 00:00:00 | - |
| Performance | 0.613 | 0.0169 | 0 |
| Gradient | 1.38 | 0.00173 | 1e-07 |
| Mu | 0.001 | 1e-06 | 1e+10 |
| Validation Checks | 0 | 6 | 6 |

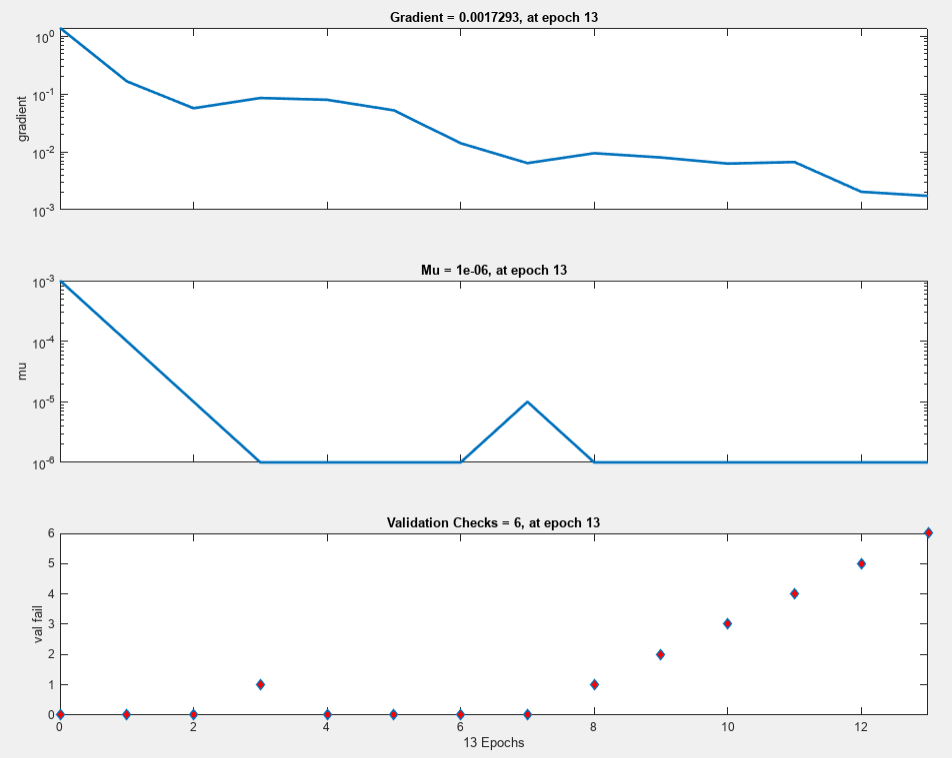


Figure 4.29 Training state of 10-layer neural network with magnetometer-assisted data

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Figure 4.30 Validation plot of 10-layer neural network with magnetometer-assisted data

A graph of error

Description automatically generated

Figure 4.31 Error histogram of 10-layer neural network with magnetometer-assisted data

Table 4.21 20-layer training results of magnetometer-assisted data

|  |  |  |  |
| --- | --- | --- | --- |
|  | Observations | MSE | R |
| Training | 4604 | 0.0170 | 0.2669 |
| Validation | 987 | 0.0185 | 0.2605 |
| Test | 987 | 0.0163 | 0.1899 |

Initial results of a 20-layer neural network on magnetometer-assisted data (Table 4.21) shows that while the MSE readings indicate that the neural network can determine the correct results, the low R values show that the neural network is not able to understand the relationships of the data. The training results of the 20-layer neural network do not differ much from the 10-layer neural network, indicating that increasing the layers of the network model alone is not sufficient to resolve the data relationships. Either the dataset is too small for the neural network to understand the relationships or some data is missing that would permit the neural network to understand the dynamics involved.

<TBC> Use magnetometer here and see what happens. Add all IMUs in to give extra data.

### Examining forward (rotating) movement.

As programming the robot to travel a straight-line path (with roll and pitch motions) was not possible due to time constraints on developing the necessary control program, the robot was programmed to travel forwards in an anti-clockwise circular (rotational) direction, and then would travel backwards, clockwise, to the starting position.  
Results from this experiment are split in to two figures for clarity. Figure 4.32 shows the Kalman filter results against the robot arm movements and Figure 4.33 shows the Madgwick filter results against the robot arm movements. Note that magnetometer data was not used in this experiment.

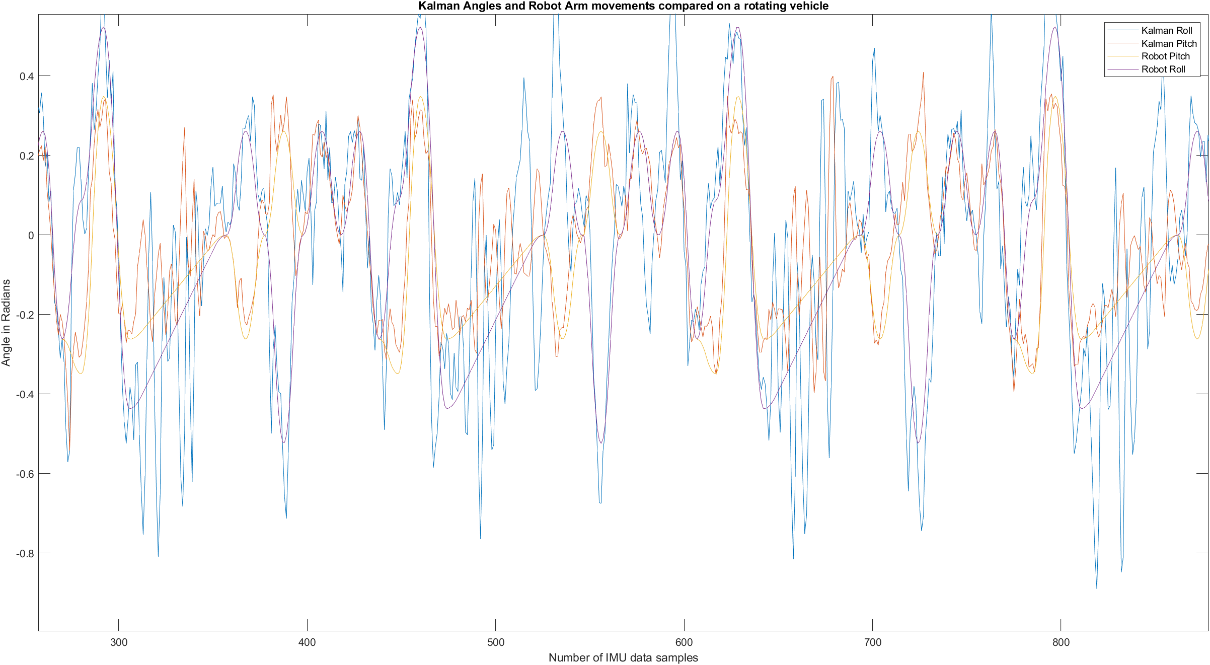


Figure 4.32 Kalman and robot arm angles compared while robot arm rotates

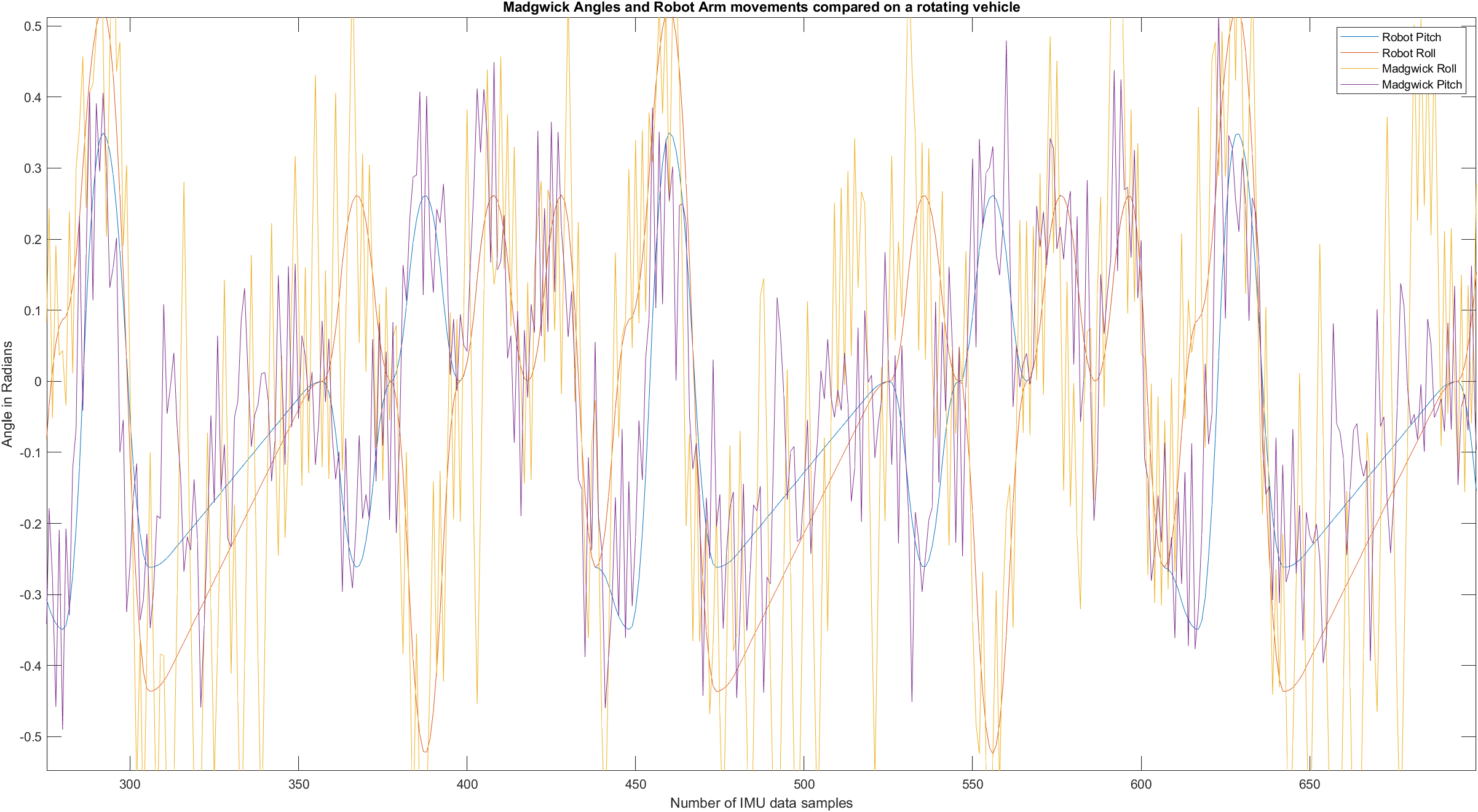


Figure 4.33 Initial Madgwick filter and robot angles compared while rotating – samples from 1-999.

Both Madgwick and Kalman results, while not perfect, are somewhat close to being acceptable once noise is removed.

The 10-layer neural network training results from the IMU data is shown in Tables 4.22 and 4.23 and Figure 4.34.

Table 4.22 Training results of 10-layer Neural network trained on rotating movement

|  |  |  |  |
| --- | --- | --- | --- |
|  | Observations | MSE | R |
| Training | 4137 | 0.0013 | 0.1768 |
| Validation | 887 | 0.0021 | 0.1759 |
| Test | 887 | 0.0013 | 0.1161 |

Table 4.23 Training Progress of 10-layer neural network trained on rotating movement

|  |  |  |  |
| --- | --- | --- | --- |
| Unit | Initial Value | Stopped Value | Target Value |
| Epoch | 0 | 12 | 1000 |
| Elapsed Time | - | 00:00:01 | - |
| Performance | 0.259 | 0.00128 | 0 |
| Gradient | 0.744 | 5.58e-05 | 1e-07 |
| Mu | 0.001 | 1e-07 | 1e+10 |
| Validation Checks | 0 | 6 | 6 |

A screenshot of a graph

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Figure 4.34 Regression plot of 10-layer neural network under rotation

Increasing the layers to 50 showed worse results, as shown in Table 4.24, indicating that the type of neural network model is either under or over training and so either the model does not fit the data and/or the data is insufficient for the neural network to determine the relationships.

Table 4.24 Training results of 50-layer neural network under rotation

|  |  |  |  |
| --- | --- | --- | --- |
|  | Observations | MSE | R |
| Training | 4137 | 0.0015 | 0.2754 |
| Validation | 887 | 0.0017 | 0.0913 |
| Test | 887 | 0.0007 | 0.0693 |

Using the magnetometer to assist the neural network produced the results shown in Table 4.25.

Table 4.25 Training results of 10-layer neural network under rotation with magnetometer assistance.

|  |  |  |  |
| --- | --- | --- | --- |
|  | Observations | MSE | R |
| Training | 5190 | 0.0089 | 0.2901 |
| Validation | 1112 | 0.0091 | 0.2640 |
| Test | 1112 | 0.0083 | 0.2488 |

The results have improved but the R values are still very low.  
  
Training with data from all 5 IMUs gave the outputs outlined in Table 4.26 which shows an improvement, but the R values are still too low.

Table 4.26 NN Training results of all IMU data under rotation with magnetometer assistance.

|  |  |  |  |
| --- | --- | --- | --- |
|  | Observations | MSE | R |
| Training | 5190 | 0.0084 | 0.3131 |
| Validation | 1112 | 0.0084 | 0.1999 |
| Test | 1112 | 0.0110 | 0.2683 |

Using backpropagation training instead of LVM gave the output shown in Figure 4.35. The R values are somewhat lower than from using the LVM training method.

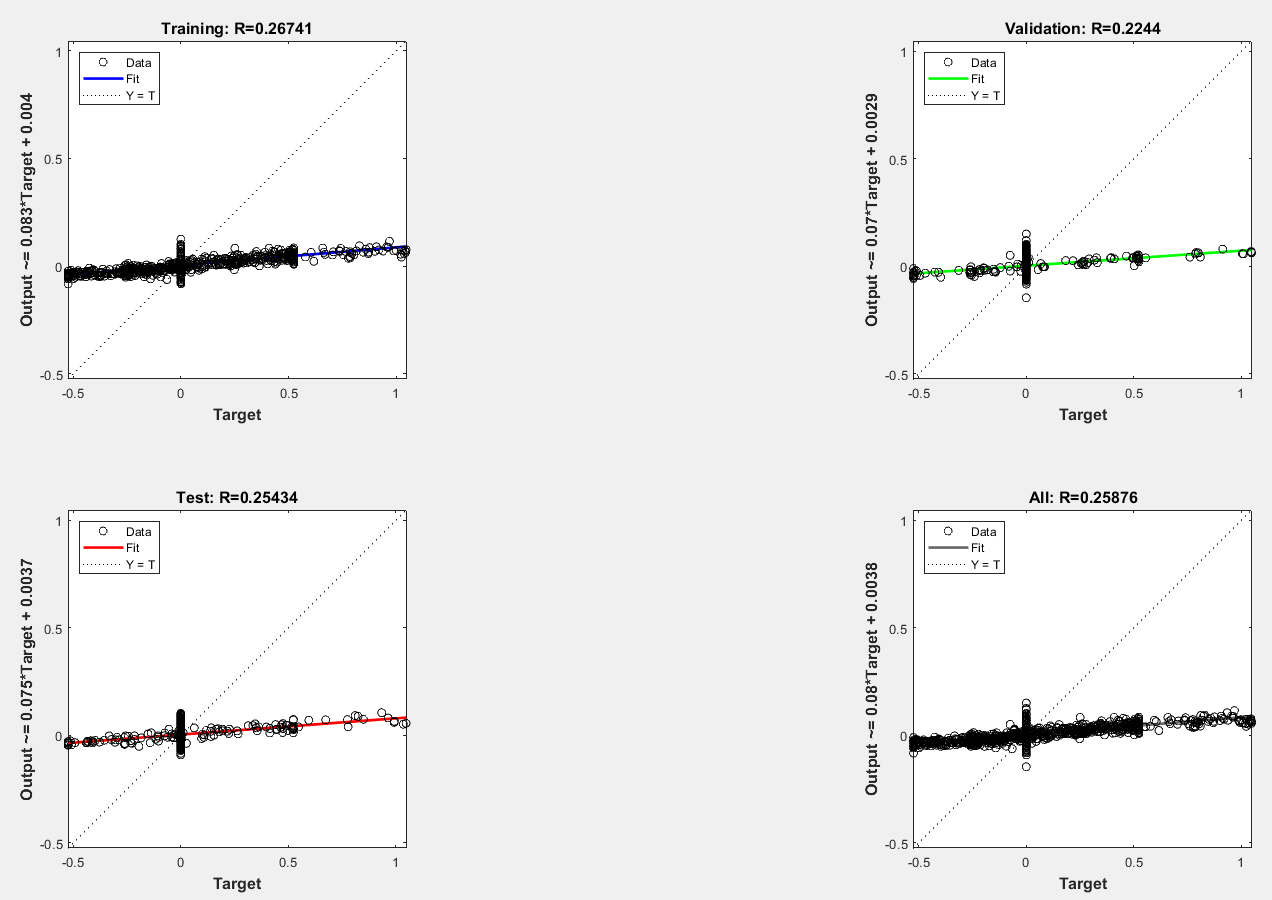


Figure 4.35 Using back-propagation training instead of LVM

### Exploring an IMU (front-left) installed upside down with varied movements.

Placing the front-left IMU upside down while the chassis underwent varied roll and pitch movements produced the following results.

### Exploring rear IMUs mounted at 90 degrees from the forwards direction.

Keeping the front-left IMU upside down, the left-rear IMU was turned 90 degrees to the left and right-rear IMU was turned 90 degrees to the right and the experiment repeated. Results are shown below.

In Chapter 5, analysis of the results is undertaken with conclusions reached in Chapter 6.

# Discussion and Analysis

## Experimental Design Analysis

First, the experimental design and implementation needs to be discussed.  
  
The overall design concept is sound and very good neural network results were achieved but implementation can be significantly improved by removing the requirement for an I2C multiplexor, and ideally, utilising individual SPI connections to increase the data collection rate, instead of the original I2C implementation**.** The selected IMUs do not support a Universal Asynchronous Receiver-Transmitter (UART) interface – if this is available on an IMU, then it is suggested that the UART be utilised in preference to the I2C and SPI bus topologies.

At least one IMU should be implemented at 90degrees, vertically, to enable the capture of data that can be used to ascertain yaw movements. Time did not permit the construction of a mount that would achieve this. It is advisable that at least two IMUs be used; one in a conventional direction and one at 90degrees vertically, with the x-plane (roll) facing either upwards or downwards as this arrangement should capture the most information with the least cost.  
  
The potential for TCP/IP collisions when collecting data (a minor factor in data alignment but easily mitigated) can be addressed by direct connections from individual network cards.  
  
One possibility to increase the accuracy of timing alignments is to provision two time-synchronised computers, one directly connected to the vehicle-processor and the other directly to the robot arm. Using reliable and consistent time-stamped data would decrease the time necessary to manually align readings and it is possible that this can be automated.   
  
Reducing the number of processes running on the computer to the absolute minimum assisted in generating reliably-time-synchronised data. It is to be noted that this timing concern is only of importance for verification that the system is performing well and is not required in operation. It is expected that, in production, the processor will be running other tasks such as vehicle control and route-planning, etc, meaning truly accurate timing is not possible.  
  
The aluminium and plastic baseboard design was proposed to ensure the IMU sensors all operated on the same plane with maximum rigidity to make comparisons simpler but it is likely that IMU sensors will be directly mounted to the panels on a vehicle. If a single baseboard is to be used to eliminate multiple plane concerns, then this should be changed to a non-magnetic rigid material such as acrylonitrile butadiene styrene **(**ABS) plastic, to enable the use of the onboard magnetometer on the IMU, especially where less ferrous material might be located nearby to make a magnetometer data usable, such as at the rear of the vehicle (assuming front-wheel drive).  
   
The robot arm provides predictable angles once calibrated however the robot joint construction and arm length does not easily permit roll and pitch modifications while travelling in forward/reverse directions except for small distances. As such, this experiment does not consider roll and pitch movements while under any form of direct forward/reverse motions although it does examine rotational movements in forward and reverse directions. The robot arm is also only capable of moving at 250mm per second without generating faults and this is not reflective of the higher accelerations that a production vehicle is likely to experience. The robot arm polling program appears (by experimentation) to be limited to 500Hz sample rates to obtain predictable timing polling periods. The maximum sampling rate of the computer was utilised for all these experiments (approximately 4603Hz) and is likely to have heavily influenced the timing phase differences between the computer timings and the robot arm timings. Future experiments should restrict robot arm polling to a rate that is officially supported by the robot arm and/or switch to a direct connection such as Universal Serial Bus (USB) or a serial port.

Ideally, a track should be designed with accurate angles so that the effects of forward motion while the vehicle is undergoing pitch and roll movements can be analysed. The time constraints of this experiment did not permit the construction of such a track that is long enough to give a good set of data useful for training purposes. The measurement apparatus will need to include a means to verify vehicle angles (strobe-camera/pressure sensors, etc) because the vehicle contains oil-filled suspension and Wishbone suspension springs so determining the actual position and rotation of the vehicle chassis will be challenging as it can’t be based upon ground-angles alone. A track design of this configuration was not in scope, however future projects should investigate this style of experiment to verify vehicle chassis movement under pitch and roll conditions while travelling forwards.

## Filter results analysis.

The results section shows that using a Madgwick complimentary filter with gradient-descent optimisation to fuse gyroscope and accelerometer data to predict roll, pitch and yaw values is somewhat accurate when the timing of the datasets are predictable but, over time, this approach would need to be “reset” every so often to prevent the accumulation of errors, especially when the vehicle will change its speed when responding to local conditions. While this issue can be partially explained by the inconsistencies of the alignment of the imu and robot arm data, in operation, these timing inconsistencies are likely to be present, due to processor scheduling. It is recommended that a Madgwick filter be implemented only if the sets of movements can be predicted/determined so the gradient descent algorithm does not over or under fit. This finding matches the results of Caruso (Caruso et al., 2021) where they outline that parameter selection is critical for filter-based sensor fusion approaches.

The Kalman filter approximates the robot arm control movement slightly more accurately than the Madgwick and does not appear reactive to the length of the data samples fed into it but overshoots on changes of angle and takes at least 7 times the processing power (this will vary depending on the processor implemented). Reducing the overshooting behaviour will almost certainly alter responsiveness to change (this is a classic filter dynamic) and would most likely need to be adjusted to the vehicle’s speed to optimise the value.

Of the two filters, the Kalman is preferable for a long-range rover to avoid the sampling size conditions of the Madgwick filter, despite the additional processing overhead and overshooting complications.

## Neural Network results analysis.

A default multi-layer perceptron (MLP) 5-layer neural network with sigmoid functions in the hidden layers and a linear function in the output layer appears easily capable of determining Euler angles from gyroscope and accelerometer data from a single imu without any optimisation.

The addition of extra layers and of adding 2 and then 4 IMU units to the neural network inputs did give slight improvements but these are not statistically significant. This is most likely because the additional IMU data is not adding much more information than the camera IMU, as the neural network will already have determined the relationship of the camera IMU position to the desired results (including noise and drift measurements). If the IMUs were mounted on different frames, or if the frame was not completely rigid, then it is likely that additional IMUs would give useful information, but these approaches were not explored.

With more complex movements, the differences between the filters and the neural networks becomes noticeable. While the Madgwick and Kalman filters can determine the Euler angles in a broad sense, the neural network struggles to understand the relationships. This is usually because the neural network either does not have enough data or the data is missing information. Adding both extra IMU data and magnetometer information did slightly improve results but the low R values are still insufficient for real-world implementation. That increasing the number of inputs improved the model only slightly indicates that the amount of data is insufficient or the model is not correct.

In Chapter 6, conclusions and future recommendations is discussed.

# . Conclusion and Future Works

The research objectives have been answered through this experiment.  
  
Research Objective One was to determine whether multiple inertial measurement units (IMUs) in conjunction with a neural network can improve image stabilisation of a camera on an RC vehicle, compared with a single IMU. The experiment has shown that multiple IMUs offers little benefit compared to a single IMU when all IMUs are in the same plane of reference.  
  
Research Objective Two was to determine the least number of inertial measurement units required to provide a significant measurable improvement. The experiment has proven that one IMU is sufficient to provide roll and pitch data and it is surmised that a total of two IMUs should be sufficient to derive roll, pitch and yaw Euler angles if the second IMU was mounted 90 degrees vertically with respect to the first IMU, however, this last supposition needs to be evaluated.

Research Objective Three was to determine the least number of layers a neural network might need in order to provide accurate roll and pitch data from IMU inputs and the experiment has ascertained that a minimum of 3 layers is required and 5 is recommended.

# 

# 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 |

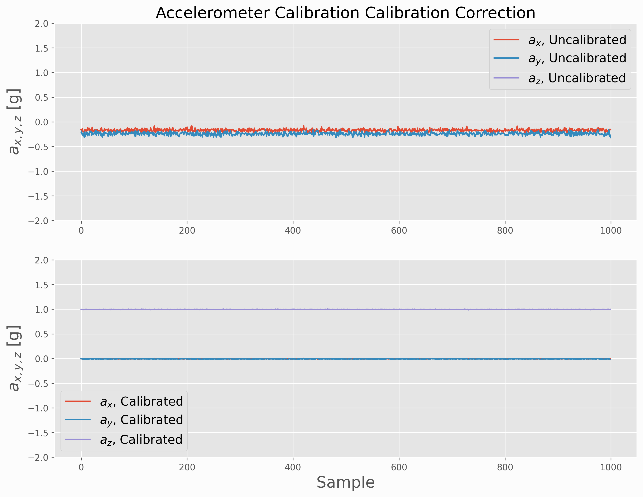
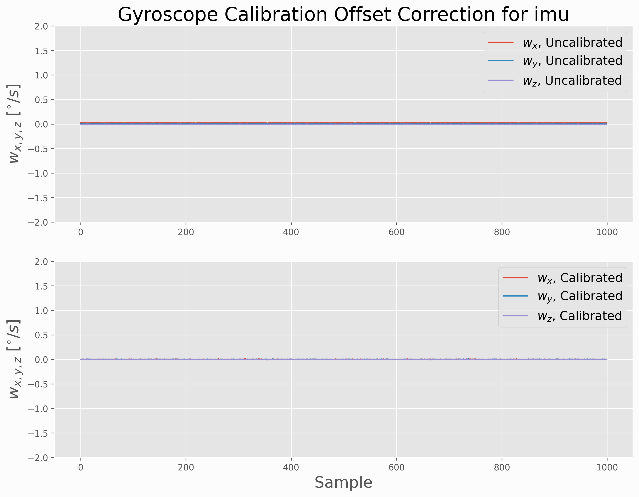
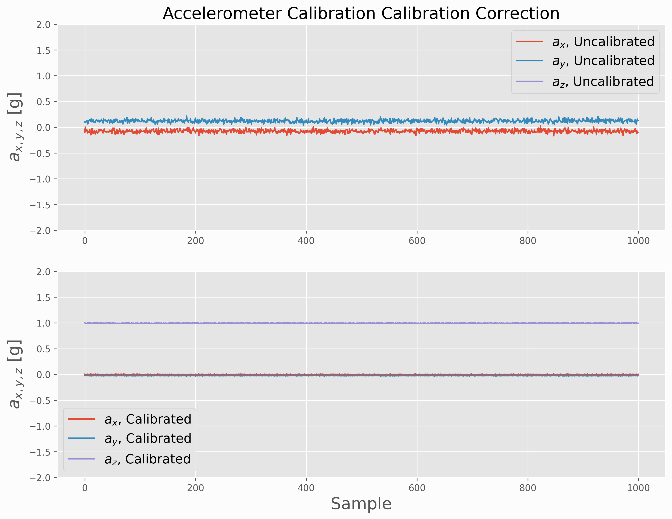
  


Figure 7.1 IMU Calibration graphs for Central Camera IMU

Figure 7.2 IMU Calibration graphs for Front Left IMU

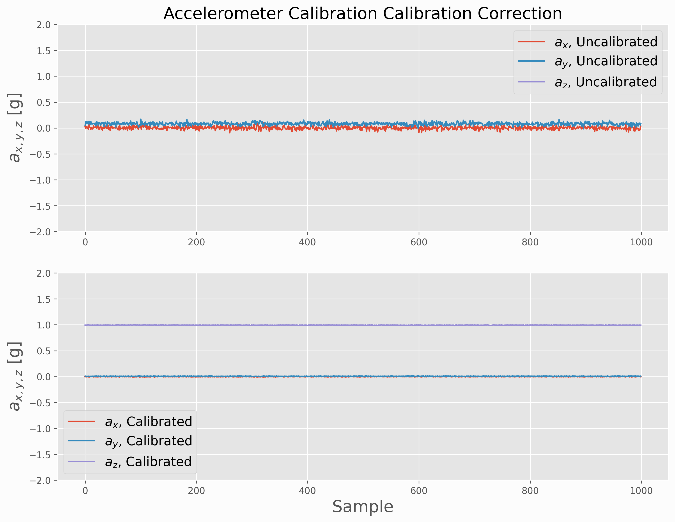
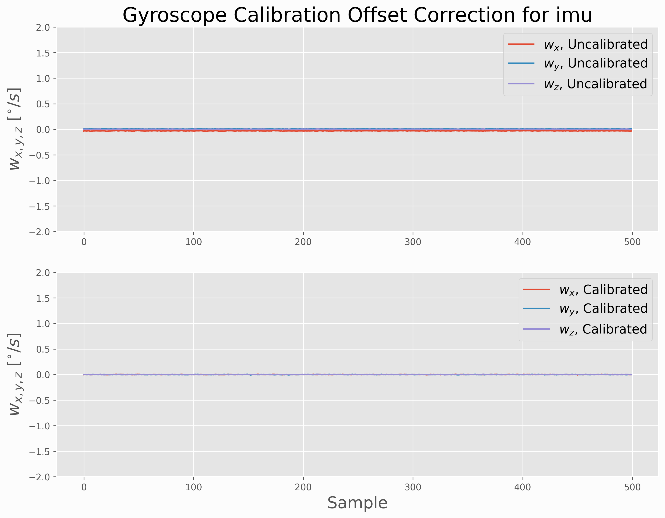


Figure 7.3 IMU Calibration graphs for Front Right IMU

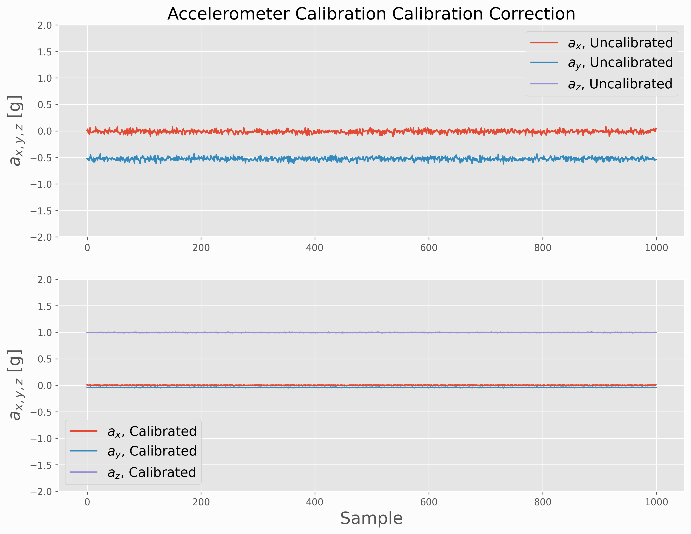
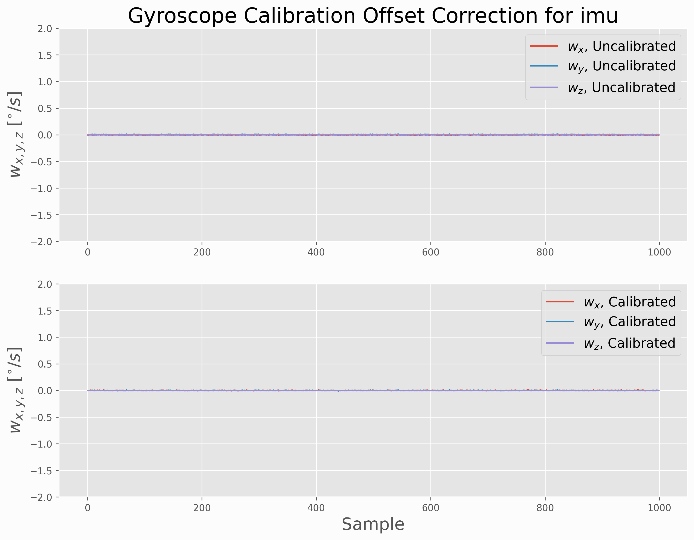


Figure 7.4 IMU Calibration graphs for Rear Left IMU

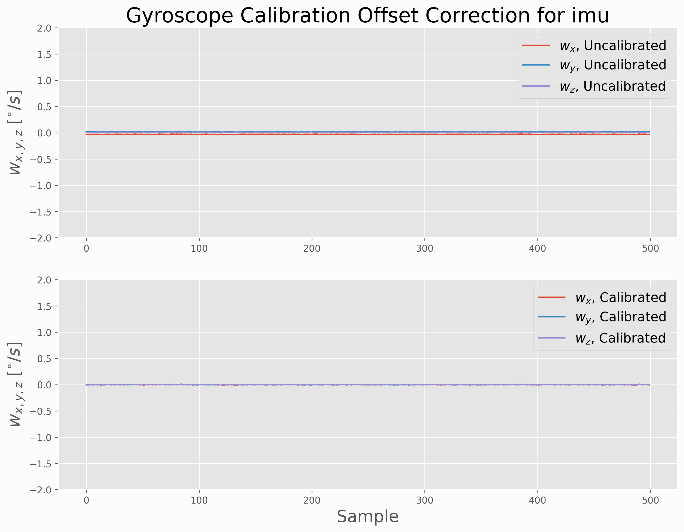
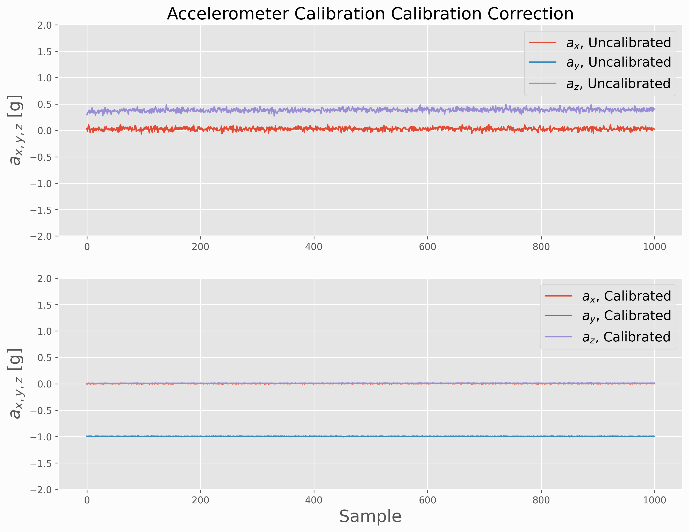


Figure 7.5 Figure IMU Calibration graphs for Right Rear IMU

## Appendix 3. Equipment Specifications.

The Raspberry Pi computer selected to capture IMU data is a Raspberry Pi 4b 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).   
Python 3.9.2 is used for data capture on the Raspberry Pi. Additional python modules to be installed are sparkfun\_qwiic (i2c support), sparkfun-qwiic-tca9548a (to drive the multiplexer), board (to simplify addressing) and adafruit-circuitpython-icm20x (to communicate with the ICM-20948 IMUs). Finally, scipy (apt install python3-scipiy) and numpy and matplotlib pip libraries are installed as these are used in the calibration script. The maximum I2C sampling rate of 1Mbs is selected.   
  
All IMUs are comprised of Sparkfun IMU-20948 chipsets (Sparkfun, n.d.). The gyroscope is set to a range of ±250rps, the accelerometer is set to a range of ±2g, and the magnetometer has a fixed range of ±4900µT.

A Sparkfun TCM9548A I2C multiplexor (required as ICM-20948 IMUs only have two configurable I2C addresses) connects all IMUs to the Raspberry Pi’s I2C bus on the default I2C pins of GPIO2 and 3. Ports 0,3,4,5 and 7 are used.  
  
To power the equipment, a 65W, 30Ah USB battery pack is used to power the Raspberry Pi, which powers the sensors and multiplexor.  
  
A Universal Robotics UR5 robotic arm provides the “ground truth” of correct angles that is used to verify the filter and neural network results. Position status is obtained over TCP/IP calls using a Python ut\_rtde module running under an Ubuntu Windows Services for Linux container on a laptop.

The Laptop used is an HP Elitebook 850 G8 laptop with 16 Gb of RAM and an i7-1165G7 Quad-core CPU running at 2.8GHz. The operating system installed is Windows 10 Pro 22H2, build 10945.3448, running the Windows Experience Feature Pack version 1000.19044.1000.0. There was some difficulty in installing the ut\_rtde robot arm software for Python (wheel dependency issues) on the laptop so an Ubuntu Services for Linux container was run on the Laptop and this container was used to launch the GetRobotData.py program (Appendix 1) which connects to the robot arm via TCP/IP and polls the robot arm for position information. The laptop connects to the Raspberry Pi via ssh to provide an interface to run the imudata.py script.  
  
To process the IMU data, MATLAB 2023a (64bit build 9.14.0.2206163) 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 processing and analysis.

The Madgwick filter selected is the freely available MATLAB implementation provided by the author of the filter. The “Initial release” version of this code was used (dated 28/09/2011). (Madgwick, 2009). An initial Beta gain (ratio of accelerometer to gyro data used) is set to the recommended value of 0.5. The accelerometer values are normalised to the gyroscope values internally within the algorithm. There are separate methods within the code. The first, UpdateIMU, is used for accelerometer and gyroscope data only, and the second, Update, also adds support for magnetometer data. MATLAB wrapper scripts were created to call these functions.  
  
The Kalman filter selected is either the MATLAB-based “imufilter” or the “ahrsfilter” (used with magnetometer readings) with default settings unless specified otherwise. MATLAB wrapper scripts were created to call either function as appropriate.

## Appendix 4. IMU-29048 IMU specifications

|  |  |
| --- | --- |
| 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 |  |

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