SOAR

STATE-OF-THE-ART REPORT (SOAR)
DECEMBER 2020

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VEHICLE NAVIGATION: AUTONOMY THROUGH GPS-ENABLED AND GPS-DENIED ENVIRONMENTS

By Carolton Tippitt, Alex Schultz, and Wesley Procino
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State-of-the-Art Report

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Carolton Tippitt is a data analyst on the System Analysis and Exploitation (SA&E) team and has worked with various data types, including RGB and IR imagery and hyperspectral data. He has participated in several large-scale data collects, where he performed multiple tasks, including collecting ground truth, analyzing, and labeling data. As part of the SA&E team, he produced several labeled datasets and performed data preprocessing on imagery datasets and was an advisor on generating and labeling algorithms during phase I. Mr. Tippitt holds a master's degree in physics.

ALEX SCHULTZ

Alex Schultz is a principal investigator with a diverse research and development background ranging from electrofluidic-based optical and display devices to advanced desalination devices and automated control systems to advanced surveillance and detection systems. He has a deep interest in system autonomy and applying advanced principles of deep learning and artificial intelligence to realize advanced system autonomy. He led the development of very small form factor aerial payloads, including electro-optical/infrared systems for the DP-3, which were ruggedized at under 5 lb and successfully test flown by the Army customer. Dr. Schultz continues to serve as a technical lead and architect for follow-on payload efforts and advanced electrofluidic devices and automated control systems.

WESLEY PROCINO

Wesley Procino developed measurement and imaging systems with high-performance cameras and optics, assessing different imaging arrays for commercial markets and government missions for maximizing cost efficiency per customer needs. He has developed and demonstrated a missile-seeking sensor in the 1–5-µm range and has also coupled image and data systems with processing algorithms for spatial, color, and spectral characteristics. Mr. Procino's software developments also include RSCube Spectral Imaging software used in flight operations for commercial and scientific remote sensing, collecting GPS and inertial navigation data for generating localized data products.

ABSTRACT

This state-of-the-art report (SOAR) discusses current and future technologies and techniques for ground and aerial navigation under Global Positioning System (GPS)-denied environments. GPS is an inaugural part of modern navigation and, when spoofed, can have costly outcomes—missed objectives, crashes, and consequences for people and property. This SOAR describes general autonomous approaches for unmanned systems, with added detail for driverless ground vehicles and unmanned aerial systems to mitigate spoofing and operate completely without GPS.

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SECTION 01 INTRODUCTION

1.1 WHAT IS THE DIFFERENCE?

1.1.1 Automatic, Autonomous, and Artificial Intelligence (AI)

To understand the difference between automatic, autonomous, and AI, let us look at standard (manual) vs. automatic transmission vehicles. Most modern vehicles are automatic, where gears shift as the driver increases and decreases speed. Alternatively, a manual transmission requires the driver to take action to execute a gear change for optimum vehicle operation. The automatic transmission decides when to change gears and what direction to change them based on sensor data that corresponds to driver operation. Automatic transmissions still require a degree of human interaction, such as changing the speed in a vehicle.

Autonomy removes human interaction from a process. Autonomous vehicles have the capacity to make limited decisions, which normally fall to a human operator. An example would be reading a speed limit sign and adjusting the speed accordingly. Understanding information such as speed limit signs is relatively easy with a machine vision model that detects stop signs. However, what if a sudden storm hits? How does an autonomous vehicle decide when a storm is too dangerous to continue to move through?

AI is a broad branch of computer science focused to train computers to make decisions like humans. The decision-making works for ranges of vehicles in different applications, adapting for land, sea, and aerial vehicles (shown in Figure 1-1).

With AI, an autonomous vehicle makes decisions, such as whether to continue through a storm, go around, or turn back—the decisions of a human operator.

Figure 1-1. Autonomous Navigation Applied to All Vehicles: Land (Left), Air: Unmanned Aerial Systems (UASs) (Center), and Water (Right) *(Source: Defense Visual Information Distribution Service [DVIDS]).*

1.1.2 Guidance, Navigation, and Control

The terms guidance, navigation, and control are often blended together into one concept, but they are truly three distinctly different functions.

1.1.2.1 Guidance

Guidance provides the reference trajectory. It includes information such as position, velocity, and acceleration of the vehicle. This state vector of the vehicle with heading bearing is a reference for the path or trajectory to move along.

1.1.2.2 Navigation

Navigation is the path required to arrive at a destination. Systems and devices such as Global Positioning System (GPS), gyros, radar, etc., provide information to plot a course.

1.1.2.3 Control

Control gives the state of the vehicle and provides options for the operator to consider keeping on the desired trajectory. If a vehicle drifts off its planned course, the controls supply information on how to get back on course.

1.2 WHAT ARE AUTOMATED VEHICLES?

The U.S. Army Engineer Research and Development Center (ERDC) issued guidelines for autonomy levels for unmanned systems (UMSs) in 2014 [1]. "Levels of Autonomy and Autonomous System Performance Assessment for Intelligent Unmanned Systems" was drafted to assist for testing and evaluating the following vehicles (shown in Figure 1-1):

- Unmanned and autonomous ground vehicles
- Unmanned aerial vehicles (UAVs)
- Unmanned maritime vehicle systems

The guidelines help with reliable testing of the safety and performance of UMSs for the armed services and define messages, a framework for modeling and architectures for autonomous vehicles.

Similar definitions have been applied to driving vehicles by the National Highway Traffic Safety Administration (NHTSA). According to the NHTSA, a fully automated vehicle is one where "the vehicle is capable of performing all driving functions under all conditions" [2].

Figure 1-2 outlines the NHTSA scale to grade and define vehicles' automation.

From the NHTSA scale, we see most cars and trucks are Class 0 automated vehicles. Technologies like automatic braking systems (ABS) and traction control assist are not considered advanced driver assistance. To be a Class 1 automated vehicle, the vehicle must have features like automatic emergency breaking, rear cross traffic alert, lane centering assists, etc.

When Tesla debuted their Autopilot, it was a Class 2 vehicle. The driver had to keep his or her hands on the wheel and monitor the surrounding environment. With new software and hardware updates, Class 3 autonomous vehicles could soon be available.

1.3 BENEFITS OF AUTOMATED VEHICLES

Automated vehicles provide numerous benefits, bridging diverse industries. For the automotive industry, automated vehicles can provide a safer and less stressful commute to and from locations. Automated vehicles also have immediate awareness and more information than a typical driver. Cars can have up to 360 degrees of vision and knowledge around the vehicle body. A human driver tends to focus mainly on objects in front of the vehicle. The driver turns for direct vision, with help through mirrors for limited sight awareness of the side and rear vehicle. Even with turning and direct looks, a driver is still seeing a small amount of the true environment. Automated vehicles use an array of sensors to gain awareness in all directions.

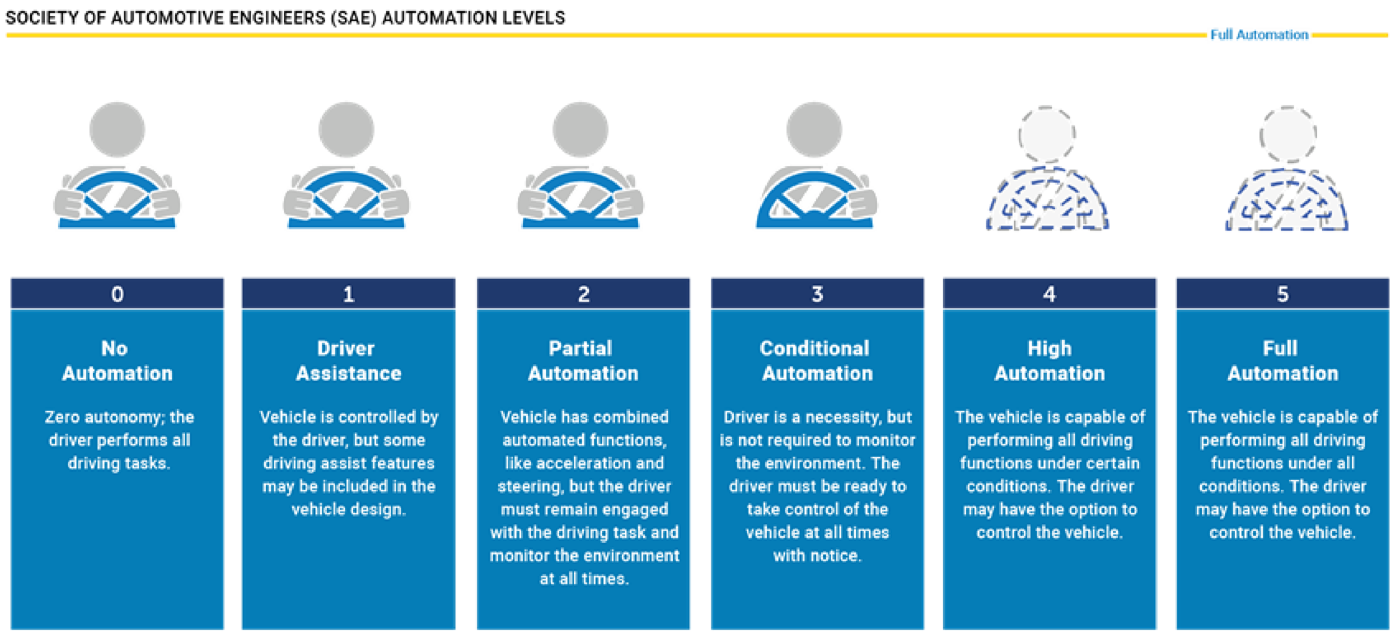
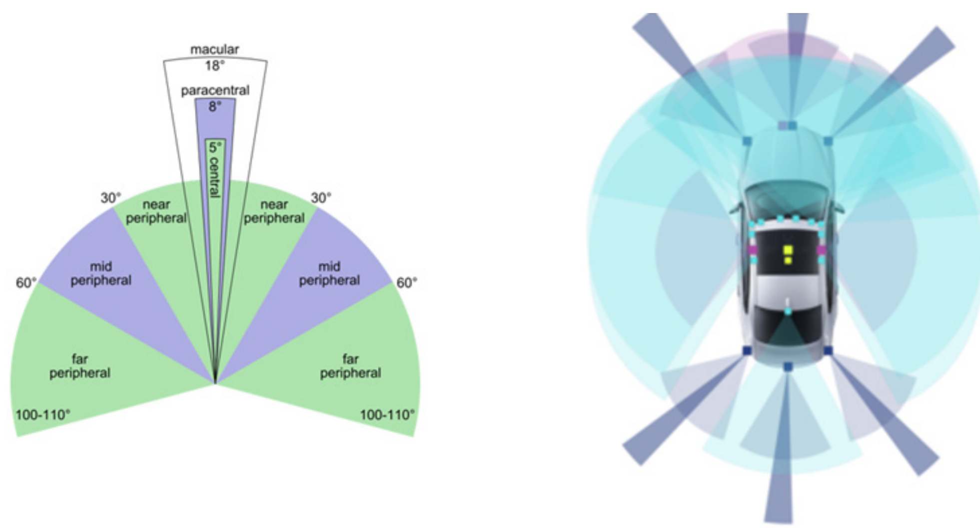


Figure 1-2. NHTSA Groups' Vehicle Automation by Capability, With Descriptions for Each Level [2].

As shown in Figure 1-3, the automated vehicle has a distinct advantage of seeing all angles of its surroundings at once. Other potential benefits are multiple sensors looking in the same direction for redundancy and overlap. If a human is blinded by a bright light, it could be minutes before his or her vision returns to normal. If an automated vehicle has one sensor that gets "blinded," it may have others that can still see and safely drive the vehicle.

Manned and unmanned aircraft equipped with the Terrain Avoidance Warning System (TAWS) [5] can really show their benefit during adverse conditions and limited visibility. TAWS is common on com-



(a) Top Down View of Human Vision [3]

(b) Simulated, Automated Car 360-Degree Vision [4]

Figure 1-3. Comparison of Human Vision (a) and Simulated Computer Vision (b) [3, 4].

mercial aircraft but not yet required by the Federal Aviation Administration (FAA) on larger commercial helicopters for passenger transport.

Other benefits of automated vehicles take advantage of visual localization and mapping algorithms using simultaneous localization and mapping (SLAM) methods. SLAM may or may not need references for preloaded maps or digital elevation maps. This class of automated systems has the advantage of working both with and without GPS, using sensors to locate positions from features of terrain, littoral zones, elevation, or any other available features and man-made structures. Without *a priori* localization information, some automated vehicles build their own maps, with passes through an area.

1.4 SENSORS AVAILABLE TO UMSs

UMSs are equipped with sensor pods that employ a variety of electro-optical, infrared (IR), and active radar sensors for target indication across frequency bands for improved sensing of locations and situational awareness from nearby natural objects and possibly man-made, approaching objects or threats.

Modern sensors for UASs are sensitive to size, weight, and power (SWaP) requirements for smaller platforms and aid flight duration of systems with limited fuel or energy supplies.

Active light detection and ranging (LiDAR) systems are deployed on UASs for day or night for mapping urban environments, terrain features, and other areas of activity, as shown in Figure 1-4. LiDAR three-dimensional (3-D) data provide information for digital and physical models for many uses, including municipal planning, urban rescue, disaster relief, and development of strategies for tactical maneuvers.

Before and after comparisons of urban and terrain features can assess mission effectiveness, completion of tasks, damages, and debris fields—any number of metrics on operations or natural disasters.

Use of LiDAR on long-duration aerial vehicles can loiter to provide time-sensitive information for progressions of conditions and monitor changes of movement.

1.5 DIFFERENCES BETWEEN GPS-ENABLED AND GPS-DENIED ENVIRONMENTS

GPS is a satellite base positioning system developed by the U.S. government. These satellites continuously send a radio signal containing the time, data, and location of the satellite (Figure 1-5). Since these are radio signals, they can be easily blocked or jammed. When this happens, the environment is considered a GPS-denied environment. In these environments, navigation is impaired for vehicles that rely on GPS for navigation.

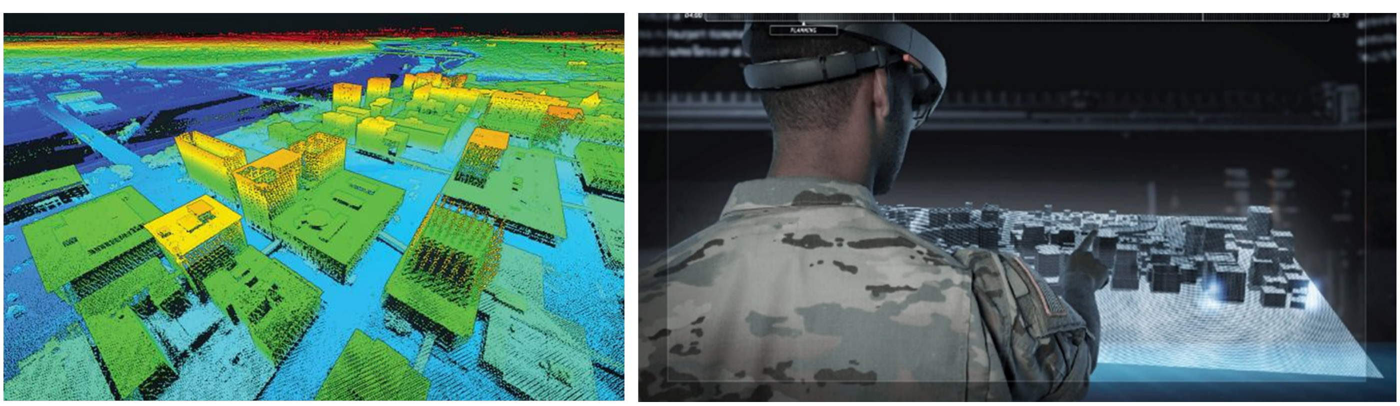


Figure 1-4. LiDAR 3-D Data (Left) and Physical Models (Right) *(Source: DVIDS)*.

Figure 1-5. GPS Satellite on Its 23rd Year in Orbit *(Source: DVIDS).*

In this report, we will discuss different technologies, where they have gaps, where they excel, and when a vehicle should use these as their primary navigation system.

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SECTION 02 BRIEF HISTORY OF NAVIGATION

Long before GPS, explorers mapped the land and sea by writing and drawing what they saw. Polynesian navigators could navigate hundreds of miles without the use of any instruments, relying on the stars and the ocean [6]. Early explorers used similar techniques but also instruments such as a compass to find the direction they were heading while they traveled. During the night, they could use a sextant, but only if they could see the horizon. Watches were especially important. By knowing the time, they could approximate the distance they traveled.

Navigating at sea uses similar instruments. However, a simple watch did not keep time well enough. In 1764, John Harrison invented the chronometer, a very accurate watch not affected by the pitching and rolling of ships. With accurate time came accurate longitude location [7]. Once ships were constructed out of metal, traditional compasses could no longer point north. The magnetic field of the ship made its bearings inaccurate. Now, ships use a special compass called a gyroscopic compass. These compasses are not affected by the magnetic field of the ship or earth. They always point toward true north. Even with GPS, ships still use a chronometer and a gyroscopic compass when traversing open water.

Today, ships have many systems onboard that help them navigate. Radar and radio brought new long-range navigation. Marine vessels were no longer without communication while at sea. Long-range navigation (LORAN-A) was a low-frequency, land-based radio navigation system developed during World War II. LORAN-A worked within 600 miles of the U.S. coast. It was later replaced by LORAN-C, which had a range over 2,000 miles and an accuracy of 0.3 miles [8]. A LORAN installation, shown in Figure 2-1, has become a backup for the Global Navigation Satellite System and GPS.

Figure 2-1. LORAN Station in Raymondville, TX *(Source: DVIDS)*.

Dead reckoning with an Inertial Guidance System (IGS) can provide information about position, speed, and location without having to use celestial observation or other remote systems like GPS. It uses a Kalman filtering technique to mathematically determine navigation solutions [9].

Kalman filtering is an algorithm that provides estimates of some unknown variables given the measurements observed over time [10]. The algorithm works in two steps—prediction (or propagation) and update (or correction). Each new prediction is based on the previous predictions, which is where the high uncertainty in long periods of time enter.

This is why systems that have a large uncertainty over time are typically used in combination with systems like GPS. GPS would provide the corrections to dead reckoning, keeping the error minimal in case the GPS signal is lost, and the vehicle has to use dead reckoning as the navigation system (see section 4.1).

During World War I, aircrafts used similar navigation to land- and seacrafts. They looked for landmarks and took compass bearings during the day and used celestial navigation during the night. As marine navigation technology evolved, so did aircraft navigation. Aircrafts started using systems like LORAN and their own versions of IGS. Like ground navigation and marine navigation, aircrafts quickly added GPS navigation into their systems.

All of these systems can be used in GPS-denied environments, with some level of accuracy. Many of these systems have lower accuracy or inherent drift in their abilities to navigate. For example, the LORAN-C's accuracy of 0.3 miles is a large uncertainty compared to satellite-based systems typically within 30 ft. GPS also provides an accurate time that can be used to calibrate other systems that may have less-accurate time-keeping methods.

SECTION 03 TECHNOLOGY GAPS AND FUTURE NEEDS

Even as technology advances, there are still issues for automated vehicles that need sorting. Some of these issues revolve around the safety and security of occupants inside and outside the vehicles, while others are the accuracy of the navigation of automated vehicles.

3.1 RISKS AND VULNERABILITIES FOR AUTONOMOUS SENSING AND OPERATION

One of the biggest needs for automated navigation are detecting and recognizing objects and obstacles within a vehicle's path. Most systems rely on visual models to detect objects in the path of the vehicle. Visual models can be fooled into detection by shadows or reflections that resemble one of the classifier objects. Other potential issues include fast-changing lighting conditions. For example, going from bright sunshine into a dark tunnel or vice versa can cause camera images to be under- or overexposed, resulting in a temporarily blinded system as sensors adjust to conditions. However, sensor fusion can mitigate transient conditions and reduce the chances of an accident by combining radar or LiDAR to scan objects in the vehicle's path.

Navigating in a city or flying across a country requires an automated vehicle to know its precise location. In a city, buildings may block or reflect GPS signals to cause the location to become inaccurate. This could result in an autonomous vehicle turning onto a one-way street going the wrong direction or thinking it has arrived at its destination while in the middle of a busy road.

3.2 SPOOFING OF NAVIGATION AND VISION SYSTEMS

Spoofing is the act of deceiving a navigation system into thinking it is a different location or blocking the navigation altogether. If a visual system is designed to look for stop signs, spoofing can be as easy as covering part of the sign. This causes the system to be unable to recognize the sign.

As discussed earlier in this report, shadows, reflections, and miss categorizing objects can spoof some visual systems. Whether intentional or not, these can be hard to detect as spoofing.

3.2.1 Recognizing GPS-Denied Environments

GPS spoofing is a known issue in the shipping industry. One such incident occurred in 2017, when 20 vessels in the Black Sea reported their positions as Gelendzhik Airport, around 32 km inland [11]. These kinds of GPS spoofing are easy to detect. But what if the GPS navigation system was taken over and the control made small changes over time? Such was the case in 2013 when University of Texas (UT) at Austin students demonstrated this when they hijacked the GPS navigation systems onboard a superyacht. The students were able to fool both the captain and the GPS system into thinking there was nothing wrong and that they were on the correct heading. Even though the 2017 incident was easy to detect, it was just as large a problem as what the UT students did. When large shipping vessels GPS systems report wrong locations, they cannot dock at the ports.

This increases the chances of vessels colliding into each other or running aground.

There are three main types of GPS signal denial. They are as follows:

1. **GPS jamming** is when an attacker generates noise signals in the GPS frequencies.
2. **Denial-of-service GPS spoofing**, sometimes called "smart jamming," is when fake, authentic-seeming signals are broadcasted. These can even be blank navigation information.
3. **Deception GPS spoofing** is when a fake GPS signal mimics an authentic GPS signal to hijack the navigation system and feed false positioning and/or timing information to the receiver.

The ability to detect spoofing is still a challenge being met with innovative solutions.

SECTION 04

CURRENT SYSTEMS AND ENVIRONMENTAL USES

4.1 GPS-ENABLED INERTIAL SENSING SYSTEMS

Inertial navigation devices use Newtonian physics to aid in navigation. The two main components of inertial navigation are the accelerometer and gyroscope. The gyroscope measures the rotation angle of the vehicle. This is used to put the inertial navigation device in the proper frame of reference for the accelerometer. The accelerometer measures specific force—the sum of acceleration and the force of gravity. Inertial Navigation Systems (INSs) have three of these pairs, one for each axis. Uncertainty in these measurements grows over time and causes drift in the navigation system [12].

Newer, low SWaP Micro Electro-Mechanical Systems (MEMS)-based inertial measurement units (IMUs) are less expensive and manufacturable in large quantities than more costly, more precise gyroscope-based IMU predecessors. MEMS-based IMUs have more drift (a sensing of a movement or orientation change even when an object is stationary) than a gyro-based IMU. For MEMS IMUs to be used in navigation, multiple sensors are strategically placed around autonomous vehicles to add secondary acceleration movement measurements to supplement MEMS data for more precise acceleration and rotational angles of vehicles at each point in their path. The most common technique to combine GPS, inertial movements, and their errors from multiple sensors is Kalman filtering.

Without GPS to make corrections periodically, the error in the Kalman filter calculation will continue to grow. It is worth noting that the error is random—a vehicle using IMUs could only take the same course multiple times, and it would get back different results.

The low cost and low SWaP of MEMS-based IMUs make them ideal for smaller vehicles. Using a single Kalman filter with these devices will result in larger location errors than other types of IMUs. For higher accuracies, Kalman filters are applied to each individual measurement to limit single-axis noise and reduce compounded errors out of the MEMS IMU.

Conventional combinations of Kalman filters perform well enough for commercial applications. For a more specialized approach and more precision, a multiple model Kalman filter uses (at least) two sub-Kalman filters that run in parallel—one for altitude and gyro errors and the other for estimated position and velocity errors. The results of each are then combined using conditional probability of residual. Results from reference [13] showed better than 0.1 m/s for velocity, 5 m for position, and 0.5 m for static conditions.

4.2 GPS-DENIED SYSTEMS

4.2.1 Preconstructed Environment Technologies

4.2.1.1 Visual Mapping

Synthetic aperture radar (SAR) is a high-resolution, two-dimensional (2-D), and 3-D mapping technique that produces these maps from resolution-limited radars and the motion of the radar antenna. As the radar moves, it continuously transmits and receives radar pulses in a sweeping fashion. When each point in the radar's swath is scanned multiple times and combined with the velocity of the vehicle, a 2-D map can be generated. The resolution of SAR is half the pulse width orthogonal to the path of the radar [14]. This technique is commonly used on satellites because SAR takes advantage of the satellites' movement to increase the radar resolution. Typical resolution for SAR is 10 cm, with greater resolution possible when using an ultra-wideband radar system. In theory, submillimeter resolution can be obtained with a terahertz radar system.

SAR has major drawbacks. Since it relies on the radar's movement to produce high-resolution images, the vehicle must be constantly moving. When standing still, a map could be produced at the resolution of the radar being used. With this limitation, it is better suited for vehicles that will be constantly in motion, such as aerial vehicles. SAR is also memory intensive and has a high computational load to operate. Each radar point is sorted and stacked with the new pulse's data and processed. The computational load will increase with decreasing wavelength and increasing number of pulses per second. In a GPS-denied environment, SAR can be used to navigate vehicles by georegistration (see Section 4.2.1.3).

4.2.1.2 LiDAR

LiDAR is like radar, ranging with laser pulses instead of radio frequency (RF) waves to generate an elevation map. LiDAR is commonly used by the National Oceanic and Atmospheric Administration to map the land and seafloor and riverbeds (Figure 4-1).

Different LiDAR systems will have different resolutions, but, generally, the accuracy is 10–15 cm nadir. SAR LiDAR can navigate by georegistration and ground control points (GCPs).

During the 2007 Defense Advanced Research Projects Agency Urban Challenge, most teams' vehicles used LiDAR for obstacle detection and terrain map construction [16]. LiDAR was the main system used in self-driving cars until Tesla designed its cars to rely mostly on cameras (and possibly radar). LiDAR has the advantage of being able to distinguish a person walking vs. a person on a bike easier than visual systems. It can also determine the velocity of objects relating to the vehicle.

4.2.1.3 Georegistration

Georegistration is a technique used to match landmarks or terrain features as scanned or imaged

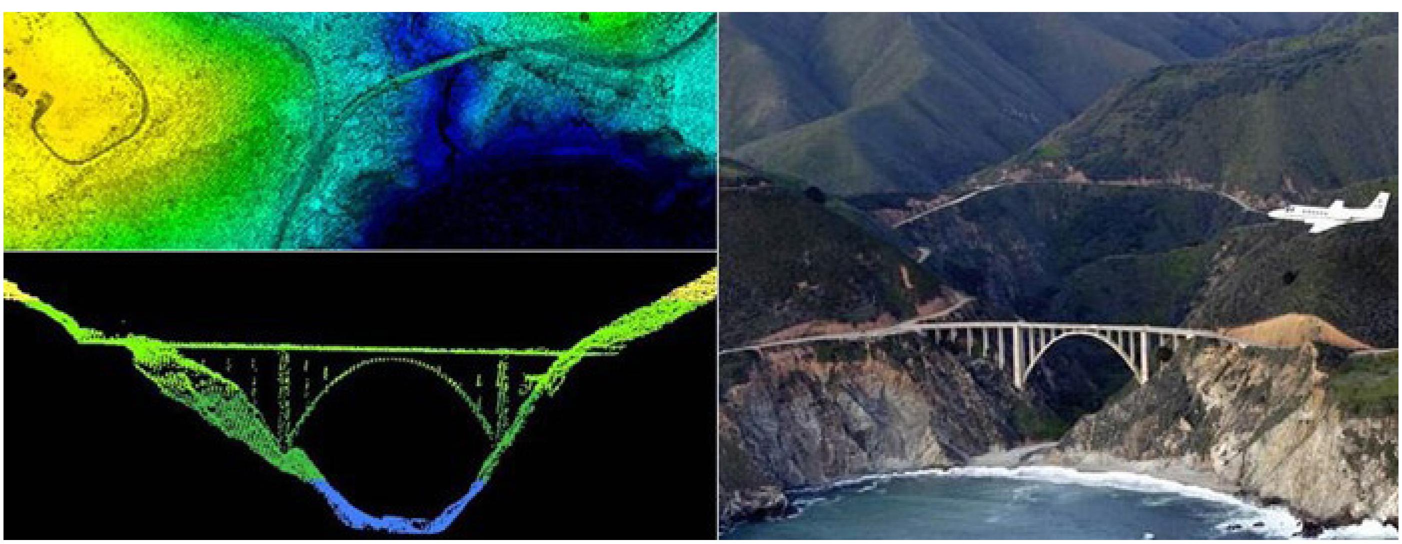

Figure 4-1. Example of LiDAR Map of Bixby Bridge in Big Sur, CA: Top-Down View (Top Left), Off-Nadir LiDAR View (Bottom Left), and Off-Nadir Red, Green, Blue (RGB) View (Right) [15].

by vehicles to preloaded landmarks or GCPs. The GCPs contain exact coordinates that are used for navigation once a match is found.

Georegistration can be used with SAR, LiDAR, and camera-based visual systems. Each sensor will use a version of feature extraction that relates well to the data type to identify possible landmarks. These features are then compared with the onboard GCPs for matches. If a match is found, the vehicle can use the exact coordinates from the GCPs for navigation.

4.2.2 Near Real-Time, Constructed Environment Technologies

4.2.2.1 SLAM – Simultaneous Localization and Mapping (SLAM)

SLAM is a set of algorithms that allows vehicles to map the surrounding environment and determine their location. Unlike georeferencing, SLAM does not need a stored (provided) map to compare. This allows SLAM to use both standard mapping techniques such as radar and nonstandard mapping techniques such as Bluetooth.

Bell Labs used SignalSLAM and GraphSLAM with mixed WiFi, Bluetooth, long-term evolution (LTE), magnetic signals, and other sensors on a phone to passively build a map and determine the location of the individual while the phone was in a person's pocket. After combining all data, they were able to reproduce the path taken. (This experiment does include GPS data from the phone; however, GPS data was not used inside buildings.) One key advantage to using a phone is most phones come with the required hardware [17].

Large-scale, direct monocular SLAM (LSD-SLAM) is another method that uses visual cameras to build a large-scale map of the environment [18]. LSD-SLAM tracks camera motion and aligns images. Coupling the motion and image predictions with filtered estimation of semidense depth maps produces a contestant map with keyframes as vertices and 3-D similarity transforms as edges. These features help detect and correct drift. An added advantage to LSD-SLAM is it can run on a central processing unit in real time, with the target running on a modern smartphone.

4.2.2.2 Radar Odometry

Radar odometry is a way of estimating the speed of the vehicle by using the radar's return signal. One such radar system is called Doppler navigation radar—custom-built radars with the sole purpose of determining velocity of the vehicle (usually aircraft). Doppler navigation radars, which are non-overlapping, use multiple beams with fixed angular differences. These systems have a disadvantage of being singularly tasked; they can only determine the vehicle's velocity. The added SWaP and complexity of adding it to a vehicle may not outweigh its benefits [19].

If a vehicle already has a SAR system onboard, it is possible to determine the velocity of a vehicle using a monopulse SAR system and the direction of arrival (DOA) of the pulse—an added capability without extra components or added weight or power. By measuring the *quint angle* to the target pixel, the radar's velocity can be measured without the need for the Kalman filter to perform the calculation. After computing the aircraft velocity and the quint angle, the following additional information can be calculated:

- Forward ground speed of the aircraft.
- Crab angle of the aircraft (the angle formed between the direction the aircraft is pointed, and the direction it is tracking is over the ground).
- Line-of-sight velocity of the radar in the direction of the antenna boresight.
- Correct azimuthal scaling of the SAR image.
- Correct application of antenna beam pattern corrections to radiometrically calibrate the SAR image.

The DOA technique was tested using a multiphase center radar, and it showed promising results.

The estimated velocity and true velocity showed a close match even when error and offsets were added to the data.

4.2.3 Deep-Learning Methods

Deep learning has had a tremendous influence on automated tasks because of its greatly improved image recognition and ability to recognize and recall objects and features in scenes. The progress in recognition has been accompanied by a significant increase in computational power available to embedded computers small enough to install on vehicles. Computations hosted on graphics processing units (GPUs) within embedded processors, with many duplicated GPU cores, has greatly advanced deep-learning methods for use in vehicle guidance and navigation.

Deep-learning navigation will only be as good as its architecture and chosen datasets. When selecting the dataset, keep these four factors in mind:

1. Should be large (more is always better).
2. Should be easy to ingest and clean.
3. Should contain a reasonable of mix of both continuous and categorical data.
4. Should contain an equal mix of all categories (object recognition).

4.2.3.1 Convolutional Neural Networks (CNNs)

A CNN is an algorithm which takes input data, such as images, and assigns weights to various aspects of the data. Once it has assigned these weights, it can identify, label, or mark the desired information. An example of image-based CNN is alphanumeric handwriting classification (Figure 4-2). Images of handwritten letters and numbers are passed into the CNN for training. Once the CNN is properly trained, images of handwritten notes can be passed into the CNN, and it will return the transcribed, handwritten notes.

Programming languages like Python, C++, MATLAB, and even Envi IDL have libraries (or packages) dedicated to deep-learning methods. Some of these libraries even have premade CNN model generators designed for nonskilled individuals to build and use CNN models. However, these premade generators do not always work with specialized data, and a person skilled in CNN will be needed.

There are many benchmark object detection datasets, such as PASCAL, VOL, and COCO; they are widely used in autonomous vehicle navigation. There are also many architectures that have shown promise for fast object detection. The focus is on these three categories of object detection—two-

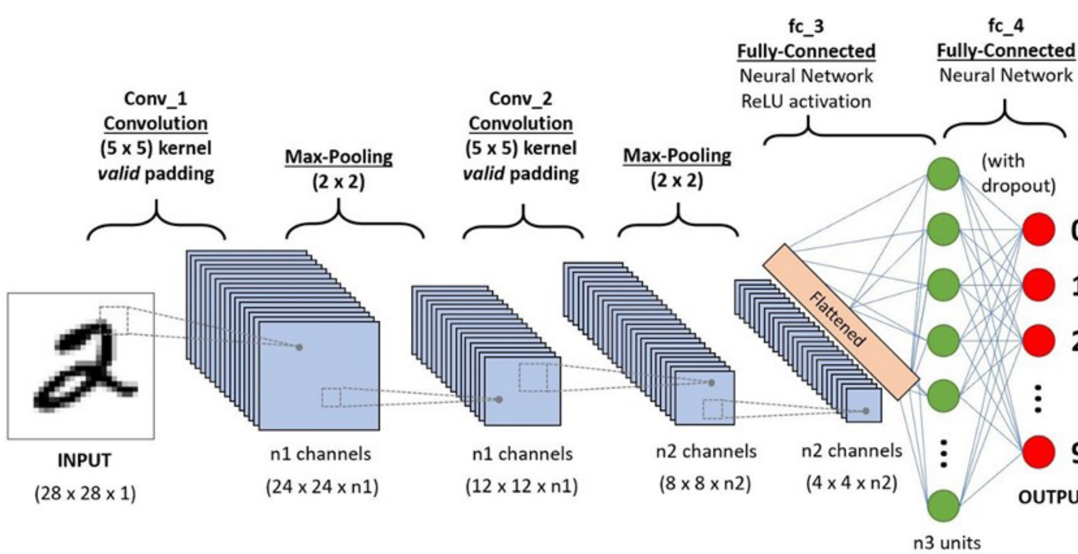

Figure 4-2. Example of Handwriting Classification CNN [20].

stage object detection, one-stage object detection, and segmentation (discussed in Section 4.2.3.2).

OverFeat and R-CNN are examples of two-stage object detection. First, these models find regions of interests (ROIs) and extract them using a sliding window approach. Once all the ROIs are found, each region is passed to the CNN to perform the object detection and classification.

YOLO, MultiBox, and SSD are examples of one-stage object detection. Unlike many two-stage detectors that have similar steps, one-stage detectors vary drastically from one another. YOLO, for example, takes the output from the CNN and regresses the bounding boxes [21], whereas MultiBox predicts a binary mask from the input. YOLO also uses regression but uses multiple feature maps of different resolutions.

Object detection and recognition is a deep-learning method used to find objects in images. It is a very popular method for finding objects in images. One of its main uses in vehicle navigation is detecting objects and avoiding them. Object detection does an excellent job at detecting people, other vehicles, signs, etc. For navigation, multiple models may be needed for the vehicle to correctly navigate.

Two-stage detectors will generally produce better detection scores because of the way they break into ROIs and allow more refined detection. However, this comes at a cost of increased inference time and a more complex training architecture. One-stage detectors tend to be faster but sacrifice accuracy.

4.2.3.2 Semantic Segmentation

Image segmentation is a form of object detection that creates a mask of each object it detects as opposed to drawing a box around the object (like object detection does). With segmentation, the image is divided into multiple parts called segments. Every pixel in the image is then labeled. This is a granular map of the scene in the image; the vehicle can now use the segmented image for improved navigation.

Segmentation can be a two- or one-stage classification problem (Figure 4-3). More common is the one-stage pipeline that uses a fully convolution network (FCN). In an FCN, the classification scores from a fully connected layer CNN are replaced with convolutional layers to produce coarse output maps [20–22].

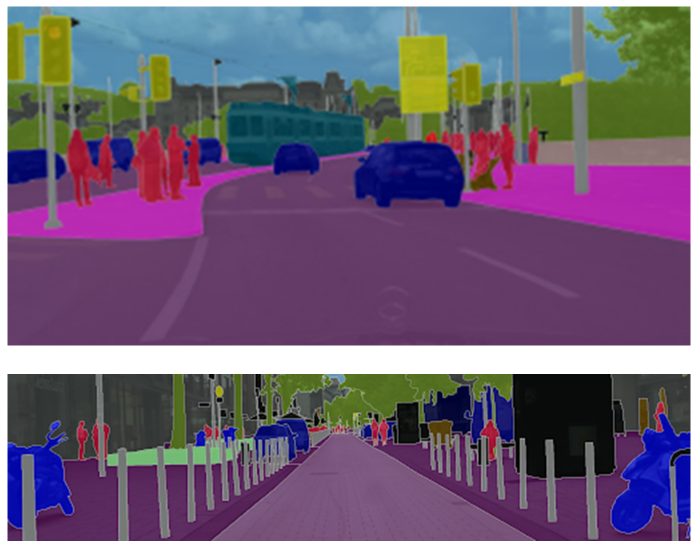

Figure 4-3. Image Segmentation (Top) and After Classification (Bottom) [22].

4.3 UNDERGROUND UNMANNED VEHICLES

Unmanned vehicles used in mining solve a number of difficulties of getting people underground while meeting extreme safety requirements under dangerous conditions.

GPS signals are obviously unavailable underground. Early underground vehicle guidance depended on approaches using surface beacons or transmitters, with coarse resolution and modest results. Low-frequency electromagnetic, ultrasonic sensing measurements were used for underground positioning and continuous tracking. Localization methods using WiFi, Bluetooth, and radio frequency identification were also used in early vehicle autonomy [23].

The underground vehicles use a SLAM method based on generalized iterative closest point (GICP), 3-D point cloud registration between consecutive key frames and loop frames to generate underground roadway maps. The method was evaluated under several conditions and compared with 3-D LiDAR odometry and mapping data.

The comparison of results demonstrates the algorithm achieves low-drift localization and point cloud map construction and is a candidate for localization and navigation of underground mining environment.

4.4 LOW-SWAP AERIAL SYSTEMS

UASs used for tactical situations with autonomous operation are optimized for SWaP. Using the U.S. Department of Defense (DoD) group definitions, the focus on low SWaP is Group 1 and 2 UASs, which need innovative and efficient counters to anti-access/area denial (A2D2) conditions (Table 4-1). Larger UASs can carry larger and more sophisticated situational sensing systems to help guide them through denied spaces (Figure 4-4).

Other small UASs loiter, utilizing intelligence, surveillance, and reconnaissance sensors for kinetic collisions or munitions delivery. Both types of tactical small SWaP vehicles require navigational knowledge for autonomy to carry out their mis-

Table 4-1. UAS Groups' DoD Unmanned Aircraft System Airspace

UAS GROUP	MAXIMUM WEIGHT (LB)	NOMINAL OPERATING ALTITUDE (FT)	SPEED (KNOTS)	REPRESENTATIVE UAS
Group 1	0–20	<1,200 AGL	<100	RQ-11 Raven, WASP
Group 2	21–55	<3,500 AGL	<250	ScanEagle, Flexrotor

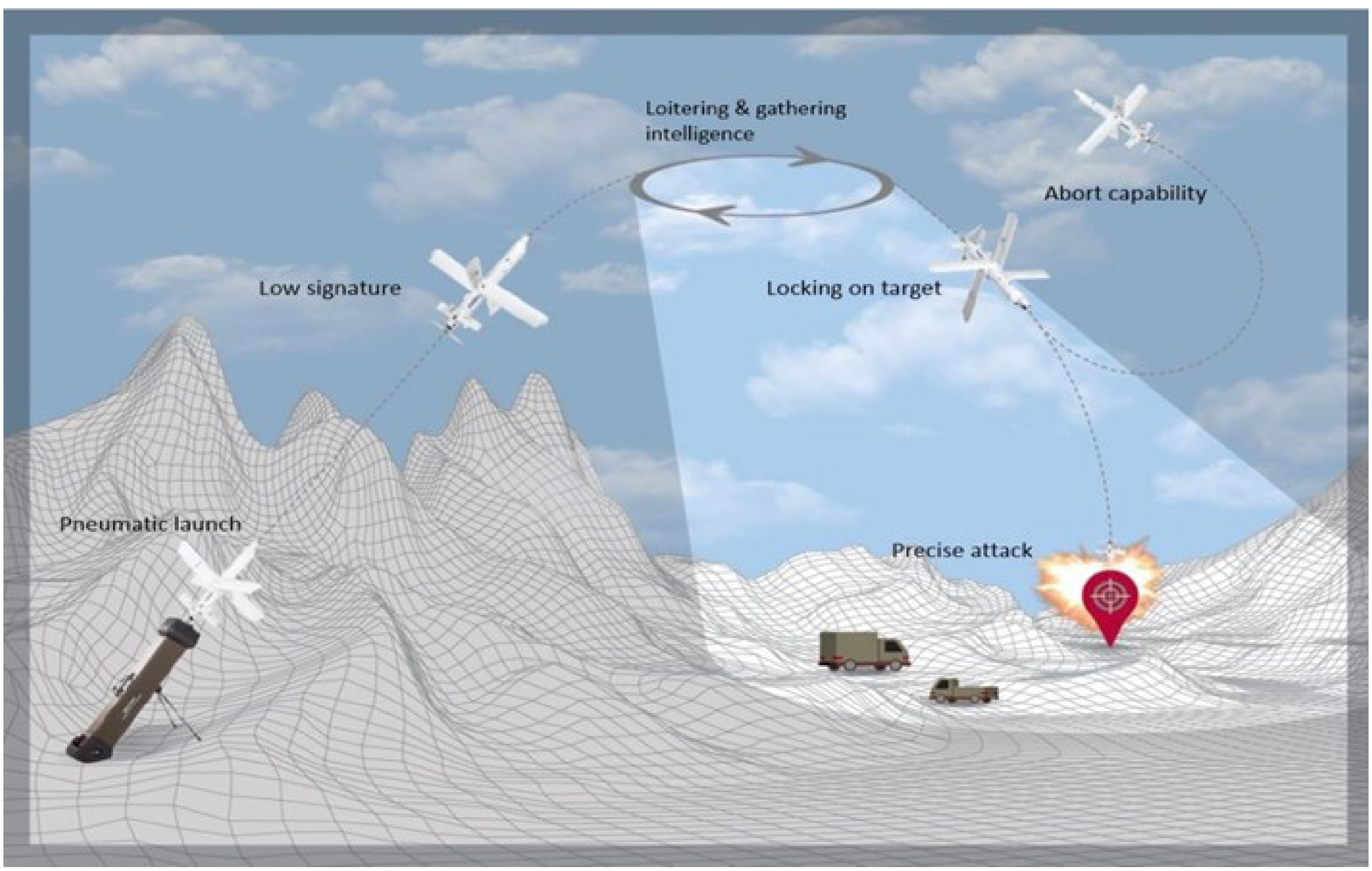

Figure 4-4. A Hand-Carried or Back-Packable Group 1 UAV With Low SWaP for Deep Remote Mission Engagement *(Source: QinetiQ Inc.)*.

sions. Embedded processors churn through data for positioning and navigation and relay information and video back to ground stations.

Extracted information and video feeds SLAM processes and other mappings for tactical situation awareness.

Some Group 1 UASs (Figure 4-2) can be trailed into remote locations and highly unpredictable circumstances, backpackable and hand launched as needed, to gain knowledge of adversary positions, assets, and numbers (Figure 4-5).

Figure 4-5. Hand-Launched Group 1-Type UAS *(Source: DVIDS).*

Group 2 UASs are larger and have different objectives, gaining endurance for persistent observations or carrying more sophisticated instruments for increased knowledge (Figure 4-6). The larger size affords more room for sensors and resolution, which may better map and correlate to stored map databases for improved positional knowledge.

Figure 4-6. Group 2 UAV – Ground-Launched With Sensors and Gimbal for Observation and Mapping *(Source: DVIDS).*

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SECTION 05 ADVANCED TECHNOLOGIES FOR FUTURE SYSTEMS

Many of the techniques and technologies in this section are based on or are extensions to those previously discussed. Most are still being tested under lab conditions.

5.1 VISUAL LOCALIZATION

A recent study in visual localization shows a limited but promising technique for navigating in GPS-denied environments. The approach uses particle filter networks (PF-net), which have many uses. Particle filters or sequential Monte Carlo methods, algorithms typically used in signal filtering to solve the filtering problems, work well with noisy and/or partial observations. The benefit to using the PF-net model is it can learn end to end through the inferencing algorithms using back-propagation gradients [24].

The vehicle (or robot in the study) was placed in a random room and allowed to move around the building. Periodically, the vehicle would use the recorded data to determine its current location. The study showed that a vehicle with a camera, odometry, and 2-D floor map can accurately determine its location. PF-nets can even use semantic maps—maps with labeled areas or rooms. With semantic maps, the vehicle could know if it is in a friendly area or a nonfriendly area. Currently, this is not a real-time localization method and does not work well for large areas. With continuing research, PF-nets could be a viable SLAM option.

5.2 NEURAL EMBEDDINGS

Neural embeddings are continuous, low-dimensional vectors that represent discrete categories connected to each other. This makes them great for finding nearest neighbors and making predictions or recommendations based on provided information. Neural networks (NNs) are the architecture that surrounds the neural embeddings. A 2014 study used an NN to detect and negate spoofing from both natural and artificial sources [25]. They tested two NN architectures—feed-forward and recurrent networks, the two architectures used for dynamic systems. The test used a GPS antenna, an RF generator, and a combiner, which fed into the GPS receiver. When testing an adaptive notch filter (ANF) cascade with a simple structure of a Σ-Π NN algorithm combination, the signal-to-noise ratio improved by about 46% and the RMS by 27%.

Neural embeddings have an advantage over other deep-learning and artificial intelligence techniques because they tend to be easier to train; if built correctly, they can learn and improve themselves over time. For problems like detecting and negating GPS spoofing, having the neural embeddings learn and adapt to the changing GPS signal environment will allow vehicles to continue to have reliable GPS signals.

5.3 SEMANTIC GEOREGISTRATION

As discussed in Section 4.2.1.3, georegistration is the ability to scan the environment around the vehicle and locate its position by matching the scans to a preloaded map. Semantic georegistration takes this one step further with semantic segmentation. The degree of segmentation is up to the algorithm developer and what is needed; however, this added information can lead to more accurate localization for vehicles. For aerial vehicles, segmenting visual sensors can allow roads and builds to be mapped instead of just prominent landmarks [26]. Augmented reality systems can take advantage of semantic georegistration. Two-dimensional images can be turned into 2.5-D and mapped to 3-D LiDAR maps. Using segmentation categories, including buildings and roads and algorithms to estimate distances in images, a 2.5-D map is generated. This map compares the estimated building height to the LiDAR 3-D map for georegistration [27].

5.4 MULTIAGENT SYSTEMS

Multiagent systems are best for distributed problems. These are problems where information, control, and/or processing are not centralized. The information typically would not be from the same vehicle but from other vehicles or systems in the surrounding environment. A good example of this is traffic management. There would be an agent for traffic signals, traffic lanes, individual vehicles, etc. [28]. Each agent would collect data, perform inferencing, and pass its results to other agents. Most research on multiagent system navigation is centered around civilian applications; however, the framework could be adapted for other uses.

5.5 QUANTUM IMUs (COLD ATOM INERTIAL NAVIGATION SYSTEMS)

Cold atom inertial navigation systems do not rely on the Newtonian physics as many INSs. Instead, they use the quantum properties of matter based on de Broglie's work [29]. De Broglie proposed that particles have wave-like properties at the quantum level, with a relationship between the momentum and wavelength. Since the particles have wave properties, they now have a phase associated with them. As the vehicle rotates, the phase will change. This is similar to how gyroscopes work, except gyroscope wavelengths and the speed of the wave are much higher than particle wavelengths. The change in phase ($\Delta\varphi$) is inversely proportional to the wavelength (λ) and velocity (v).

$$\Delta\phi \propto \frac{1}{\lambda v}.$$

The lower speed and smaller wavelengths of the matter waves give cold atom inertial systems higher sensitivity and, therefore, increased accuracy. Using the duality of the particles, the acceleration can be obtained from the flight path of the particles [30].

SECTION 06 SUMMARY

GPS has almost become a requirement when traveling from one place to another. Besides giving accurate position, it also provides updates to clocks and fixes drift in other navigation systems. Because of this, navigating through a GPS-denied environment is not trivial and requires new and innovated ways to determine precise position while traversing the area. New technologies and techniques will continue to be explored for adding in vehicles traversing these environments. Knowing the environment for which the vehicle is intended will also boost performance. Using a preconstructed environment may not be suitable for areas hit by natural or man-made disaster. Systems like SLAM or a deep-learning method would be more beneficial. Understanding how each navigation system operates will provide the best option for each situation.

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VEHICLE NAVIGATION: AUTONOMY THROUGH GPS-ENABLED AND GPS-DENIED ENVIRONMENTS

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