GNSS/INS Fusion for Automotive with Mass Market Sensors

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BIOGRAPHIES

Ryan Dixon is the Chief Engineer of NovAtel's Synchronized Position Attitude Navigation (SPAN) GNSS/INS products group. His responsibilities include enhancement of NovAtel's sensor fusion technology and overseeing the long-term direction of the product line. His knowledge and experience are in integrating inertial measurement technology, from navigation grade to commercial Micro-Electrical-Mechanical Systems (MEMS) with GNSS technologies.

Mike Bobye is a Principal Geomatics engineer at NovAtel Inc. He has a deep breadth of knowledge in GNSS, GNSS/INS integration, and was a member of the original research team that created the first GPS/INS integration at NovAtel in 2000. He has developed several patented methods for improving reliability and robustness of GNSS/INS products.

Brett Kruger is a Software engineer working within NovAtel's Safety Critical group. With his background in INS, Brett leads the development of ASIL rated inertial software targeting autonomous driving applications. Brett graduated with a MASc in Electrical engineering from the University of Toronto in 2012.

Anil Sinha is a Geomatics engineer at NovAtel Inc. His responsibilities have covered testing and development of multiple NovAtel GNSS product lines, including their line of reference GNSS receivers, Smart antennas, and SPAN GNSS/INS systems.

ABSTRACT

Autonomous driving is predicated on the ability to measure a vehicle's position, velocity, attitude and the environment around it. This complex task requires a large and varied array of sensors as well as algorithms to exploit their measurements. A major component of this is absolute positioning. Two technologies in particular are heavily relied upon to deliver the absolute position: GNSS and inertial sensors. Current production vehicles already contain both GNSS and inertial sensors, but these are used (and are therefore specified) for functions such as infotainment and stability control. Performance needed for these functions is significantly below what is required for safe lane-level navigation. This means the current sensors, and therefore positioning capabilities, are unable to satisfy the more rigorous requirements needed for autonomy. Future vehicles will need to include more advanced versions of both sensors, along with corrections and advanced fusion techniques, all at a cost level that remains amenable to mass-production. This is a significant challenge facing mass market autonomous driving.

There are already many autonomous test vehicles on the roadways, though these provide mostly level 4 autonomy or lower [1], meaning they still require a human driver to be present and operate only in certain conditions. Additionally, these test vehicles are typically using sensors which are larger and more expensive than what is acceptable for mass production. The task of these test vehicles is to prove, and gain public acceptance of, the technology while mass marketable versions are developed.

This paper focuses on the absolute positioning component using GNSS and INS technologies. Specifically on the inertial fusion using currently achievable performance using mass market sensors. A companion paper: "Precise Positioning for Automotive with Mass Market GNSS Receivers," [2] focuses on GNSS capabilities.

The synergy between GNSS and INS has been well documented and is now widely used in growing industries such as mobile mapping. Noise inherent in GNSS positions can be smoothed by the continuous INS solution and at the same time, low frequency inertial errors are controlled by the GNSS. However, when GNSS is unavailable, the INS errors grow rapidly when unconstrained. The speed at which the INS errors grow is much larger when using lower-performance mass market sensors, making the task of mitigating these conditions more difficult for the fusion solution.

Clear trends can be seen in the results showing that the type of sensor has a significant impact on overall accuracy, but so too does the fusion technology used. The effects of this are apparent though modest in the suburban highway scenario, but are much larger in the more difficult urban canyon scenario.

To evaluate the achievable performance combining mass market sensors and NovAtel's SPAN inertial fusion technology, live data was collected and analyzed. These datasets were collected using different IMUs in two major scenarios; suburban highway and urban canyon. Additionally, a simplified loosely coupled inertial filter was run on the same data to evaluate the effect of the fusion algorithms on the resultant solution as final system performance depends on both the sensors and the integration. Results are compared against a post-processed solution using a survey grade dual frequency receiver paired with a navigation grade inertial measurement unit (IMU). Percentage of solutions with accuracy under the target of "lane level" positioning will be examined in each environment.

It is clear in the results that autonomous highway driving can be very nearly achieved with GNSS and INS sensors alone, even with mass market sensors, when the right fusion technology is used. But in urban canyons, where GNSS satellites are often obstructed, or only visible via reflection, this is not the case. While sophisticated fusion technologies offer vast improvements, more development and likely more sensors will be required to meet the required accuracies at the extremely high confidence levels required for autonomy.

INTRODUCTION

The automotive industry's push towards driverless vehicles has attracted a great amount of public attention recently, being widely covered by the media. Many noteable companies, from automotive manufacturers to ridesharing services are now operating test vehicles in various locations around the world. Most of these test platforms feature high quality sensors to provide the required accuracy and reliability necessary for developing and proving autonomous vehicles. However, these sensors are typically too large and expensive to be practical as a mass-production solution. Therefore, an evolution from these sensors towards those more palatable for mass-production must occur for the technology to truly succeed.

Modern vehicles already include an array of sensors of varying sophistication which could contribute to autonomous driving systems. The end goal is to find a safe and reliable method for fusing the data from these sensors to provide a navigation solution in a functionally safe manner. Although many sensors can be used to provide additional redundancy and observations to the navigation filter, two major components are foundational to providing the absolute position; namely GNSS and INS. The scope of this discussion will be focused on these elements, and more specifically, the performance achievable with automotive (mass production) inertial sensors.

The goal of this paper is to examine the achievable performance in combining automotive grade inertial sensors with automotive grade GNSS and the NovAtel SPAN GNSS/INS filter using Land Vehicle Technology [3], but no additional aiding sensors. Challenges of using lower cost IMU sensors in an automotive environment will also be discussed. Analysis will be conducted using live data collected using a typical automotive sensor in a variety of kinematic conditions. Two target environments will be tested; suburban highway and urban canyon. Additionally, a simplified, loosely-coupled, inertial filter will be run on the same data to evaluate the effect of the fusion algorithms on the resultant solution. Results with the mass market sensors are compared against results using measurements from a NovAtel survey grade dual frequency receiver, and a post-processed reference trajectory generated from a tactical grade IMU.

The results will be provided within the context of performance required for ADAS (Advanced Driver Assistance Systems), AD (Autonomous Driving) and V2X (Vehicle to Everything). For simplicity, the common requirement discussed is “lane level” positioning, understood to be less than one metre at a 99.7% confidence, though a target performance of 0.5 metres will be held as the goal.

TEST EQUIPMENT

As the focus of this analysis is on the inertial technology, the GNSS equipment will be held constant throughout testing while IMUs of different performance levels will be used with differences analyzed.

However, it is worth briefly noting that the GNSS modules available in vehicles today are likely not representative of those that will be used in autonomous vehicles. Most current deployed receivers are single frequency and support one or two constellations. To achieve the requisite safe and accurate positioning performance, at least dual frequency with some mechanism for receiving corrections will be required. This affects both the receiver and the antenna design [2]. The GNSS equipment used for this testing includes prototype NovAtel dual-frequency automotive grade antennas and OEM7500 dual-frequency automotive grade GNSS receiver modules. They were contained in the development kits seen in Figure 1.

Figure 1 – Automotive GNSS Evaluation Kit

As mentioned, providing corrections to GNSS is also necessary to achieve lane level positioning. For these tests Precise Point Positioning (PPP) was the positioning mode. Specifically, Terrastar-X fast convergence corrections using a Regional Ionospheric Model (RIM) were delivered via TCP/IP [4]. This is a likely future deployment method for GNSS positioning to meet the required performance level in urban and suburban areas.

The inertial component is of primary interest and is the primary variable in the testing. Three IMUs are examined, representing three distinct sensor performance categories. All the IMUs tested are 6 degree of freedom (6-DOF) sensors including a gyroscope and accelerometer in each orthogonal axis. The three IMU types are as follows:

1. Automotive Mass Market IMU:
   Results presented here have been conducted with a single type of mass market IMU. These results are comparable to those achieved with other sensors in the category from established vendors. These are devices that must cost very little but are qualified to at least AEC-Q100 [5]. Automotive Safety Integrity Level (ASIL) classifications are also going to be required for deployment.
2. Commercial high-grade MEMS IMU:

Itself an emerging category of sensors, performance achievable by MEMS IMUs has increased dramatically in recent years along with the navigation filters to exploit them [3]. Though these sensors share their base technology with the automotive grade sensors, they are produced in lower volumes, extensively calibrated and held to higher specifications.

3. Navigation grade IMU:
Navigation and tactical grade IMUs based on technology such as fibre-optic gyroscopes represent another order of magnitude increase in both cost and performance (as well as size and power consumption) from their MEMS counterparts. This type of sensor is frequently used today in proof of concept autonomous systems.

IMU PERFORMANCE

A brief analysis of the estimated gyroscope biases between the different IMU sensors will serve to highlight the difficulties integrating lower cost sensors for the purposes of navigation. There are many different error sources present in IMU data [6], but the bias offset and instability provides a suitable representation of the differences in overall performance. For the purposes of brevity in the following two sections, the focus will be on gyroscope bias, but consider that these principles extend to all IMU error sources.

Unlike navigation or high-performance MEMS sensors, the turn-on uncertainty of the gyro biases of mass market sensors can easily exceed 1000 deg/h, which is a very large offset to estimate. When the bias exceeds earth's rotation rate of 15 deg/h (the static measurement) by two orders of magnitude, it becomes extremely difficult to separate the signal from the noise. This means significant rotational measurements will be required to observe the bias properly. In a vehicle, rotation measurements are somewhat constrained as vehicles on public streets may not turn very often or sharply. The net effect of this is that a prolonged convergence period may be required to reach optimal performance as the biases, non-linearities and other errors are estimated and corrected by the inertial filter.

Statistics provided in Table 1 below illustrate the magnitude of gyroscope bias between the classes of IMUs. These statistics were generated from the real-world highway test data described later. Looking at the individual biases shows that not only does the absolute magnitude of the biases differ significantly across the varying IMU grades, but the in-run stability also varies considerably. It can be easier to understand the magnitude of the bias by thinking in terms of seconds rather than hours. A bias of 7400 deg/h is about 2 deg/s. Thinking this way, it can be understood that this level of bias is not a large problem if looking for large rotations as in a phone or video game controller, but integrated over time as is required for navigation, this results in a large angular error quickly.

Table 1: Gyro bias offset and deviation for test IMUs

IMU	Mean Bias Offset (deg/h)	Bias Standard Deviation (deg/h)
Mass Market MEMS	7400	25
Commercial MEMS	100	5
Navigation Grade	0.1	0.04

It is apparent then, that estimating these biases and continually modelling their instabilities is critical to maintaining performance in any positioning application. The challenge put forth to the fusion technologies is to exploit all additional information available through initialization and modelling techniques that will alleviate as many of the issues as possible to maximize performance.

INERTIAL FILTER PERFORMANCE

As previously mentioned the IMU characteristics and proper error modelling is an important factor for achieving overall INS performance. Biases are one of the many states being estimated by the INS Kalman filter that will be solved for. However, it can take a considerable amount of time and dynamic movement for this to happen due to the size of the bias compared to incoming true measurements, especially when driving primarily along a straight path. Figure 2 below shows the normalized convergence of bias estimate when a filter begins with an uninitialized (i.e. zero) value. The values had to be normalized between the commercial and mass market sensors due to the large scale difference in overall bias size.

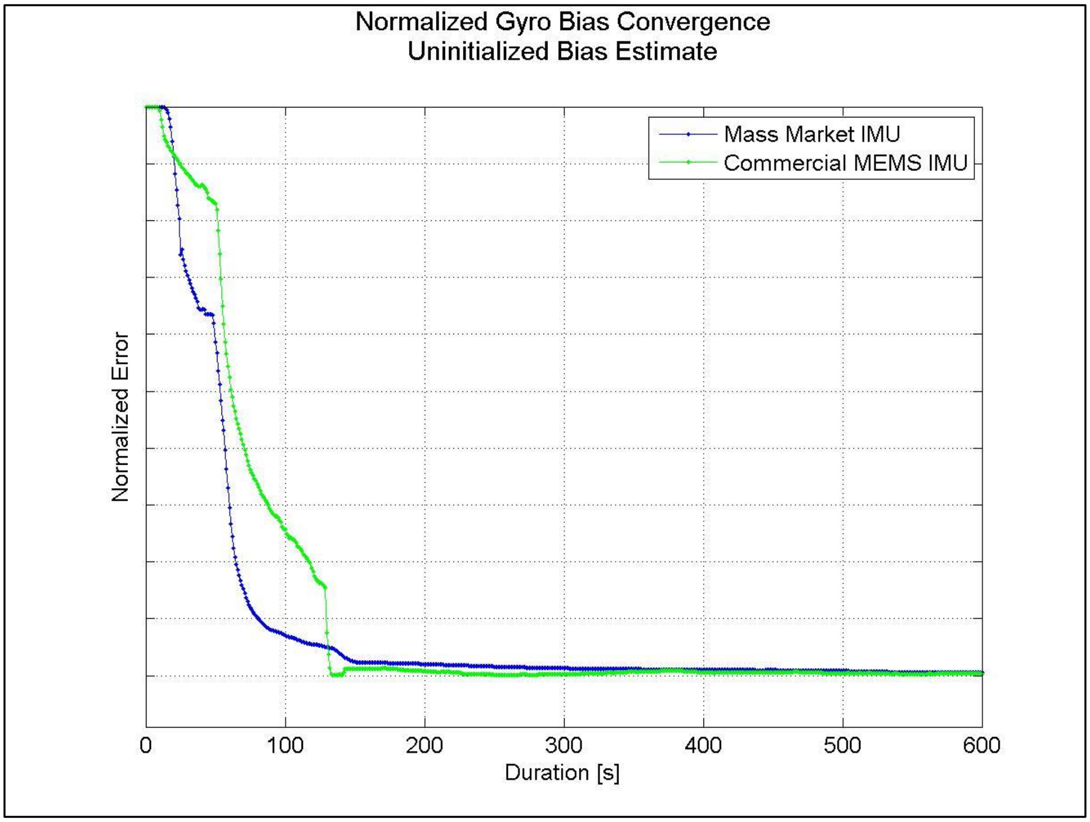

Figure 2 – Gyro Bias Turn-on Convergence

The figure shows that it can take upward of 150 seconds before the bias estimates begin to stabilize. Although the bias convergence period can be similar between the mass market and commercial MEMS IMUs, the fact that the biases themselves are an order of magnitude higher will have more of an adverse effect on the inertial solutions. As an inertial filter, such as an extended Kalman filter is essentially a filter of best fit, an incorrect bias estimate will inevitably result in inaccuracies in other states such as the position or attitude. This is best observed by looking at the azimuth convergence during the same timeframe. For this see Figure 3 below.

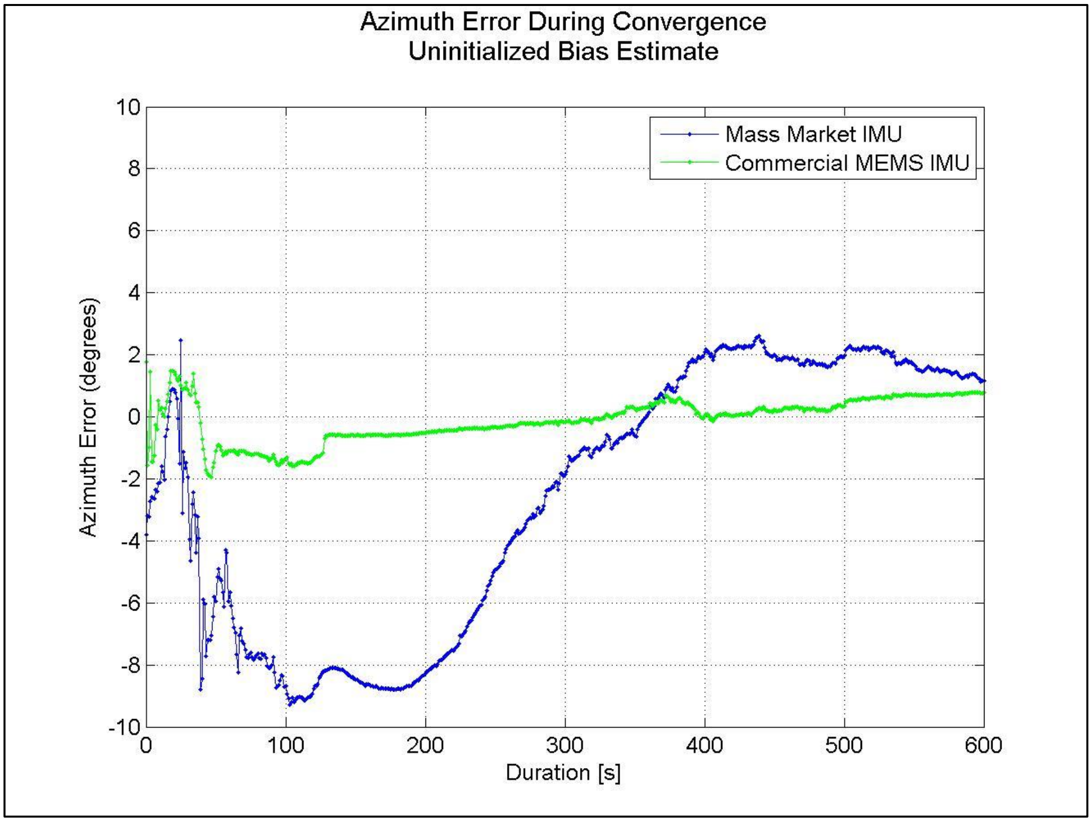

Figure 3 – Azimuth Error During Non-Seeded Initial Convergence

This shows that although the biases have stabilized after 150-200 seconds for both of the MEMs systems, the discrepancy in azimuth performance is larger for the mass market IMU during the convergence period and takes longer to correct. In this example, a fully converged azimuth solution required 10 minutes, whereas the commercial grade required significantly less time and was far better bounded during the convergence period. It should also be noted that this dataset contained high-quality GNSS coverage and dynamics during the convergence period. When GNSS is available, the attitude inaccuracies during this period have little impact on positioning accuracy, but any outages throughout this period would exhibit larger error growth for inertial positioning.

Clearly, estimating the biases and other IMU error states quickly is important to achieving desired results. In consumer markets, waiting for a period of 10 minutes after ignition for optimal performance will obviously not be acceptable. There are two well-known methods used in the SPAN engine which can mitigate this limitation. First, and potentially most effective, is to save the last known estimates to memory for recollection following the next power-cycle. This methods drawback is its reliance on the IMU retaining consistent turn-on to turn-on bias stability. This is clearly not a guaranteed condition, particularly when considering time and temperature changes between power cycles as potential factors. The second method involves exploiting any additional information to quickly estimate the turn-on biases, typically when stationary. It is important for the system to be stationary during this procedure as any undetected motion will cause anomalies in the estimated biases which can be just as bad or worse than starting from zero. Additional sensors can also provide great value here by increasing the confidence of a stationary observation or providing external motion information.

When the turn-on biases are properly handled during system initialization the convergence period is greatly reduced leading to steady state navigation much more quickly. Figure 4 shows an example of the same data as above when a previous bias estimate was injected with an appropriate variance. When this is done the convergence period on the attitude solution is virtually eliminated and the system is capable of full performance almost immediately.

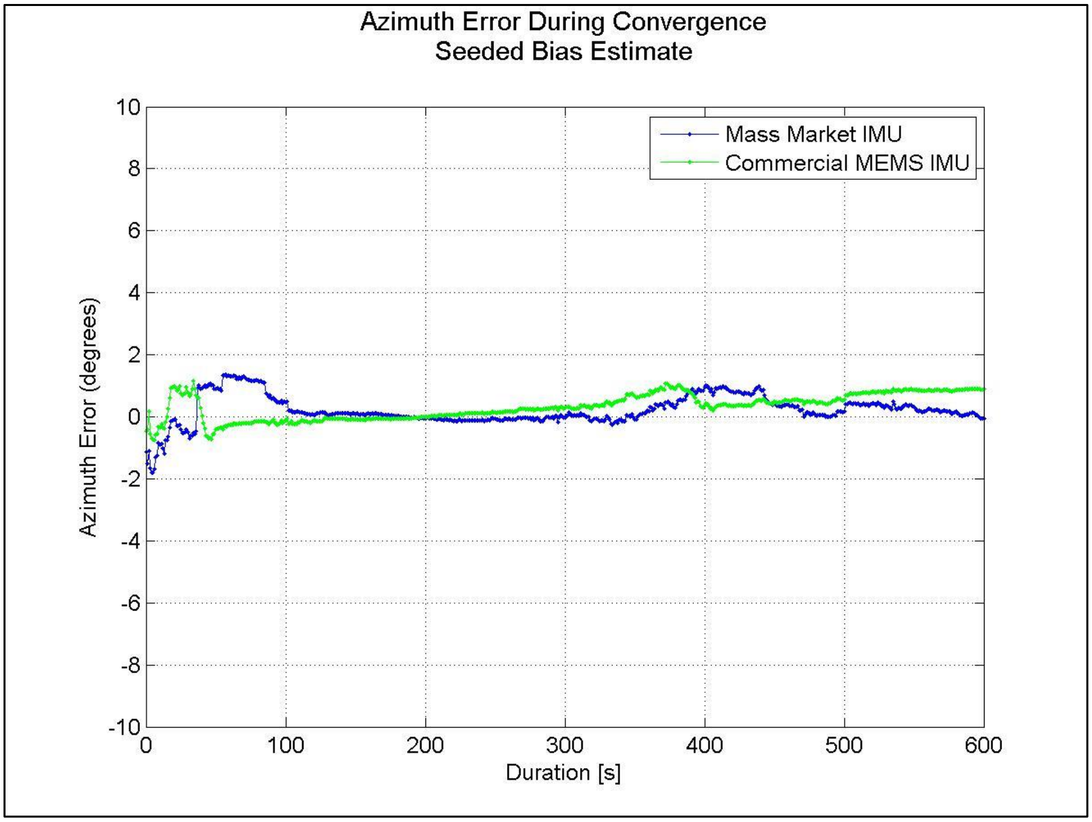

Figure 4 – Azimuth Error During Seeded Bias Convergence

This highlights again the importance of IMU error estimation when attempting to navigate via inertial measurements. An initial heading error of only a few degrees coupled with uncertainty in the error estimates can lead to dramatic decreases in overall performance as soon as difficult conditions are encountered.

Understanding the challenges inherent in using mass market sensors is critical to understanding the problem facing their use in a safety critical application such as autonomous driving. Not only is a high degree of accuracy needed, but the confidence in achieving that accuracy must be extremely high to avoid requiring the driver to manually intervene, or worse, to cause accidents. Achieving this while using sensors with such large and unstable error sources is a challenge which cannot be underestimated.

LIVE DATA RESULTS

Two test scenarios will be examined using the equipment described above; a suburban highway scenario and a more challenging urban canyon scenario. These are designed to illustrate performance in typical automotive environments and how often the solution maintains lane level positioning.

In addition to this, the IMUs will be fused with both the deeply-coupled SPAN inertial engine and a simplified loosely-coupled INS engine. This will highlight that the effect of the inertial fusion technique matters greatly, as may be expected, but that its importance also increases as the IMU quality decreases.

Horizontal position error is of the greatest importance for the automotive requirements and therefore the results will be presented using this metric. Also, with the lane-level positioning in mind, the focus will be on the percentage of solutions that meet the necessary criteria. Recall that lane-level positioning requires accuracy within at least 1.0 metre, though 0.5 metres is the target.

Suburban Highway Test

The suburban highway scenario represents conditions typical to the goal of automated highway driving within a populated area. In other words, a freeway which includes some GNSS obstructions in the form of overpasses, tunnels, and traffic congestion. The path driven for this test included four highway overpass interchanges and one longer tunnel. The northern most overpass was used to turn around and so includes several blockages in quick succession. Figure 5 below shows the path driven with the locations of the interchanges and tunnel. Six closed loops of this circuit were completed.

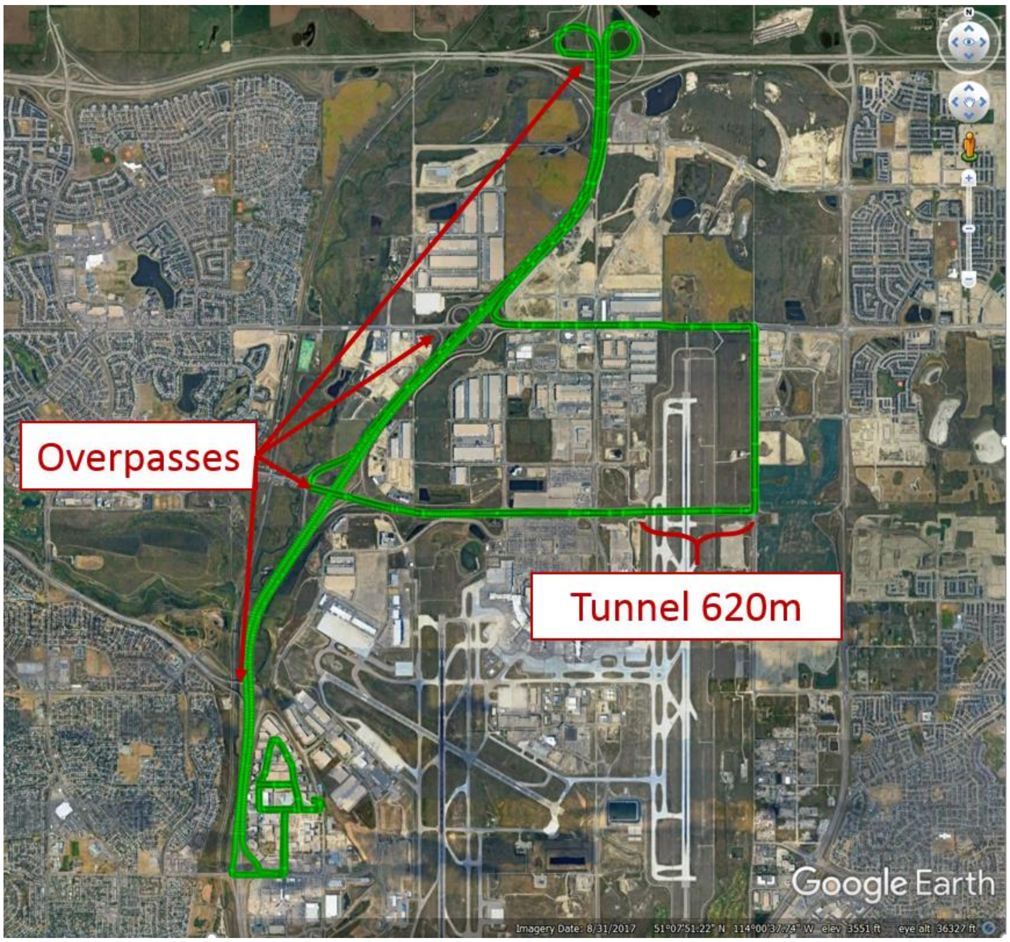

Figure 5 – Highway Test Trajectory [7]

Results of the various systems can be seen in Table 2. Because this scenario includes a sizable percentage of open sky, GNSS alone provides target performance 87% of the time, with overall solution availability of 95%. The remaining 5% of the time GNSS is unavailable due to obstructions. The majority of unavailable GNSS solutions occurs within the tunnel indicated in Figure 5. The tunnel is 620m long with an average transit time of 35 seconds (average speed of 64 Km/h). Adding a mass market automotive IMU brings the total time at the target accuracy up to 96% with a solution availability of 100%.

Due to the generally brief duration of the outages encountered, there is a relatively modest improvement in performance when using higher performance IMUs. This can be somewhat deceptive however, when considering confidence. Looking at the 99.7% confidence levels of positioning, each IMU class shows a clear improvement. Again, these maximums occurred at the end of the tunnel, or outage. See Figure 6 for a map view of this with confidence levels of each shown at the tunnel exit prior to GNSS recovery.

Table 2 – Highway Results

System	% of 2D Position Errors				99.7% 2D Position Error (m)
	< 0.50 m	< 1.0 m	< 2.0 m	< 5.0 m	
GNSS Only	86.9	93.1	94.5	94.8	2.69*
Mass Market IMU	96.4	97.9	98.9	99.7	5.12
Commercial MEMS IMU	97.4	98.9	99.7	100	1.79
Navigation Grade IMU	99.9	100	100	100	0.48

* Including only epochs with GNSS positions calculated (95% of epochs)

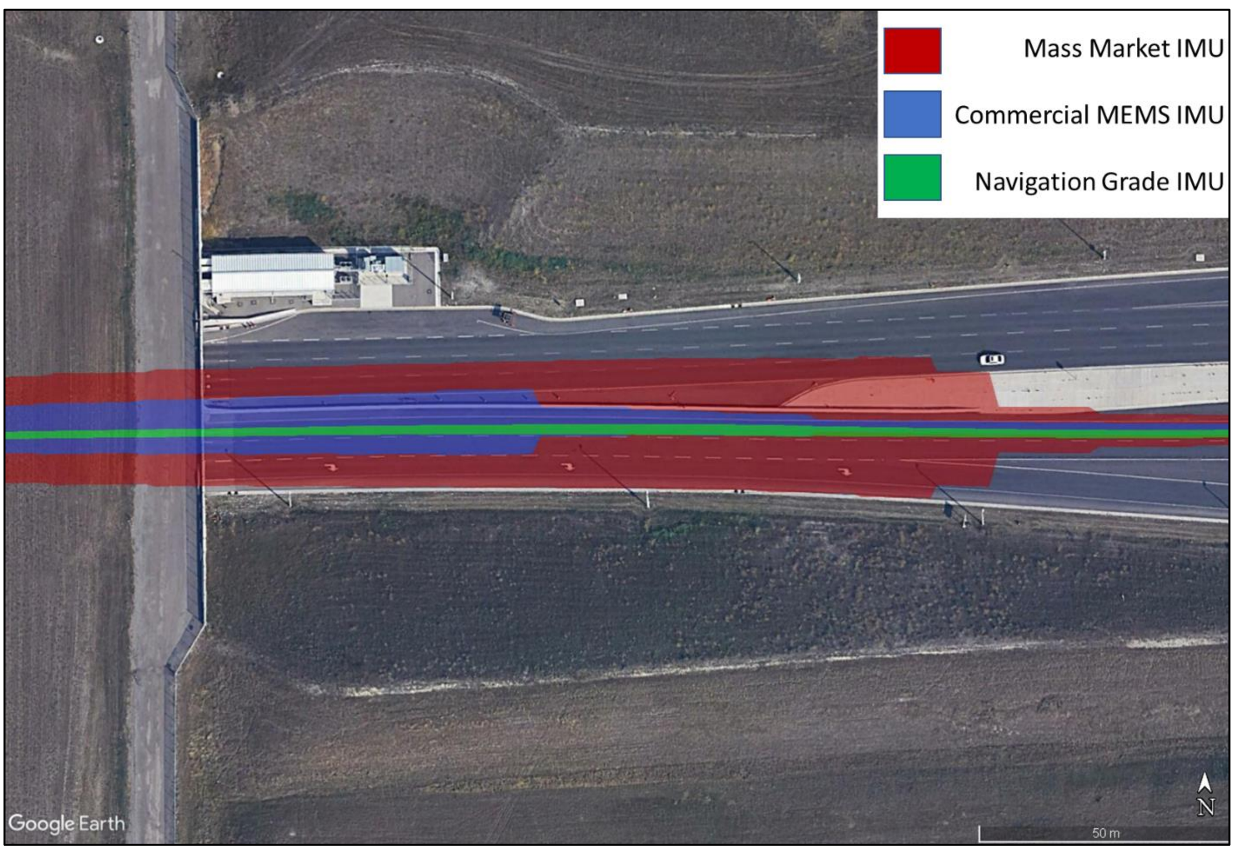

Figure 6 – Tunnel Exit Confidence Envelopes [8]

Separating the period spent under the tunnel highlights the IMU performance differences in conditions where no external updating information is available. These results are shown in Table 3, where the time periods under the tunnel are isolated. The average duration of outage in the tunnel was 35 seconds. The growth rate of inertial error is significantly different between the different IMU grades. This is expected given the very different levels of raw IMU error stabilities including, biases, scale factors, etc., discussed above. These errors cannot be estimated when removed from any external information. Of course this case is one where additional external information could be easily extracted from other sensor such as odometers or visual methods.

Table 3 – Highway Results Airport Tunnel

System	% of 2D Position Errors			
	< 0.50 m	< 1.0 m	< 2.0 m	< 5.0 m
GNSS	0	0	0	0
Mass Market IMU	33.8	54.4	75.5	92.8
Commercial MEMS IMU	49.1	73.6	94.0	100
Navigation Grade IMU	97.0	100	100	100

Though no external sensors were used, meaning no external information was available in the tunnel, non-holonomic constraints are exploited to provide some information. These constraints are applied via a “Land Vehicle Profile” in the SPAN filter [3]. So, although error growth is clear and remains differentiated by IMU class, it is much lower than would be the case without constraints. To explore this the same data will be run using a simplified loosely-coupled filter running fewer states and not using any such constraints.

The corresponding drop in overall performance using the simplified filter can be seen in Table 4. This is not an extremely challenging scenario due to the relatively short outage and the fact that GNSS was fully available and accurate heading into the tunnel and again shortly after the tunnel exit. Still, the results show a noticeable drop in accuracy across all IMUs. This is attributable to a poorer estimate of the IMU errors heading into the outage, and therefore larger growth at the end. In tougher conditions with more frequent and longer outages, these differences would begin to compound. This will be clearly observed in the urban canyon test.

Table 4 – Highway Results Airport Tunnel with Simplified Filter

System	% of 2D Position Errors (delta from SPAN filter)			
	< 0.50 m	< 1.0 m	< 2.0 m	< 5.0 m
Mass Market IMU	36.6 (+2.8)	50.5 (-3.9)	69.1 (-6.4)	90.2 (-2.6)
Commercial MEMS IMU	40.7 (-8.4)	62.2 (-11.4)	83.4 (-10.6)	100 (0)
Navigation Grade IMU	88.5 (-8.5)	100 (0)	100 (0)	100 (0)

Urban Canyon Test

Urban canyons are much more challenging for GNSS positioning, including frequent satellite signal obstructions or reflections in varying severity. This is a recognized difficulty and so most autonomous vehicles are not intended to function in these environments, at least initially. Eventually though, full autonomous navigation in these environments will be required and expected. Because the GNSS availability is much lower here, reliance upon the INS solution is correspondingly increased. Figure 7 below shows the trajectory driven for this analysis. As with the highway test, several loops of this trajectory were driven.

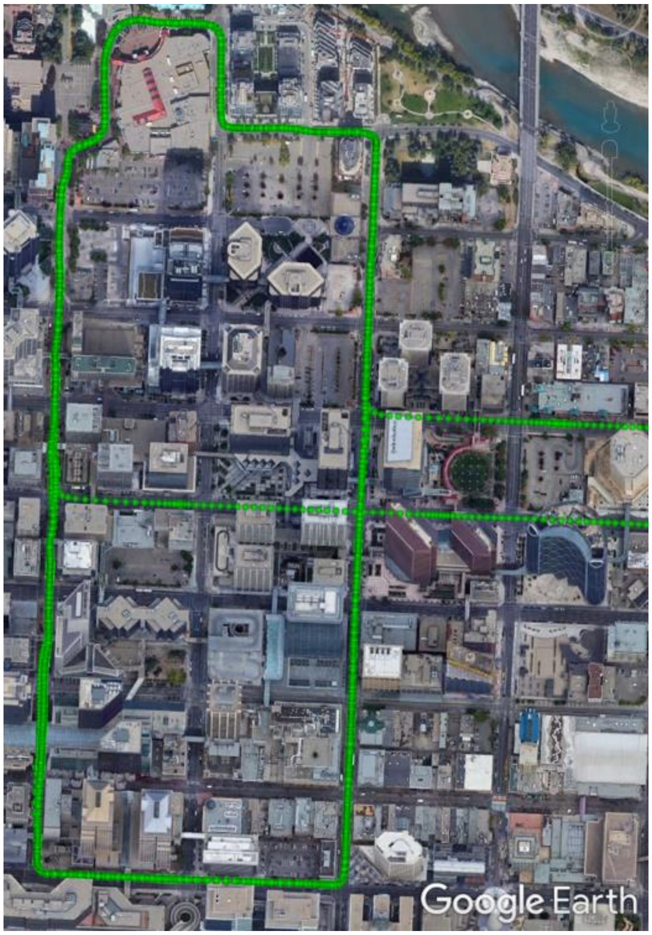

Figure 7 – Urban Canyon Test Trajectory [9]

Table 5 below shows the results of the urban canyon data collection. As expected, GNSS availability is low in these conditions due to sparsity of observable satellites, high multipath, etc. With less available positions comes occasional outliers as well.

Performance seen with IMUs increases the lane-level availability considerably, again with clear delineation between the IMU classifications. As with the highway test, all IMU solutions provided an overall solution availability of 100%, but the performance numbers show a clear differentiation in lane-level performance between classes, particularly between the navigation grade and the MEMS. In the end though, INS is a relative measurement method and because the GNSS here is frequently absent or producing solutions with several metres of error, even the navigation grade IMU cannot maintain a 0.5m positioning through the entire duration.

Table 5 – Urban Canyon Results

System	% of 2D Position Errors				99.7% 2D Position Error (m)
	< 0.50 m	< 1.0 m	< 2.0 m	< 5.0 m	
GNSS Only	6.6	15.0	20.0	29.2	N/A*
Mass Market IMU	23.7	50.6	72.9	99.5	5.41
Commercial MEMS IMU	27.3	76.1	98.8	99.9	2.82
Navigation Grade IMU	75.2	99.9	100	100	0.95

* Not meaningful with low GNSS availability

Looking again at the simplified filter, the drop in overall performance, seen in Table 6 is much more dramatic than the highway test as expected. This is due to both being able to tightly/deeply couple the GNSS, greatly increasing filter's ability to estimate and continue to model IMU errors in adverse conditions with the methods described above. Effectively continuing to model IMU errors both more difficult and more important as GNSS availability declines.

Table 6 – Urban Canyon Results – Simplified Filter

System	% of 2D Position Errors				99.7% 2D Position Error (m)
	< 0.50 m	< 1.0 m	< 2.0 m	< 5.0 m	
Mass Market IMU	9.7 (-14.0)	23.0 (-27.6)	38.4 (-34.5)	66.6 (-32.9)	59.22 (-53.81)
Commercial MEMS IMU	12.1 (-15.2)	37.6 (-38.5)	57.5 (-41.3)	84.2 (-15.7)	55.18 (-52.36)
Navigation Grade IMU	33.0 (-42.2)	76.7 (-23.2)	97.8 (-2.2)	100 (0)	2.29 (-1.34)

CONCLUSIONS

IMU technology including mass market IMUs, as well as MEMS IMUs in general have advanced dramatically in the last few years. However, their performance level remains significantly below what traditional IMUs can offer. While they can reasonably be expected to continue improving, cost and volume constraints for mass market applications likely means there is a limit to the achievable performance. This means sophisticated modelling techniques will continue to be required in order to achieve a robust positioning solution from them in any adverse conditions.

Modelling technology, such as that offered by SPAN, has been improving in conjunction with the rise of commercial MEMS IMUs and this technology translates directly to use in mass market applications. There will always be a performance cost associated with using lower performance sensors, but the improvements in fusion technology have been seen to mitigate this significantly.

In highway conditions, or whenever GNSS reception is relatively unobstructed, GNSS and INS alone can provide a solution which could allow autonomy. Though the extreme confidence levels required for safety of the public will require additional sensors for redundancy and so will still need to be part of a final solution. In more difficult conditions, this effect is the same, just more clearly displayed. In these cases, much more work is required from all the constituent parts of the solution to provide the confidence levels required.

Fusing additional devices such as cameras, LiDAR, odometers, steering angles, etc. will be necessary to provide the redundancy necessary to keep in lane positioning to a very high confidence level. Urban canyons however, struggle to achieve absolute positioning from GNSS to the required accuracy so all these relative measurement systems will struggle to refine this further. In that case, referring to high accuracy maps and/or vehicle to vehicle communication are likely also required.

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8. Source: “Figure 6. Tunnel Exit Confidence Envelopes,” **Google Earth.** August 31, 2017. August 20, 2017
9. Source: “Figure 7. Urban Canyon Test Trajectory,” **Google Earth.** August 31, 2017. August 20, 2017