Next Generation Vehicle Positioning Techniques for GPS-Degraded Environments to Support Vehicle Safety and Automation Systems

FHWA BAA DTFH61-09-R-00004

EXPLORATORY ADVANCED RESEARCH PROGRAM

Auburn University

Sarnoff Corporation

The Pennsylvania State University

Kapsch TrafficCom Inc.

NAVTEQ North America LLC

Quarterly Report 2

Jan – Mar 2010

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1. Scope

In an open environment, GPS provides a good estimation of vehicle position. Numerous improvements over the basic GPS framework have provided accuracies in the centimeter range. However, blockages of the GPS signal create significant problems for the positioning solution. In so-called “urban canyons”, GPS signals are blocked by the presence of tall buildings. Similarly, heavy foliage in forests can block line-of-sight to the satellites. Because of these problems, a broader approach is needed that does not rely exclusively on GPS. This project takes into account three key technology areas which have each been individually shown to improve positioning solutions where GPS is not available or is hampered in a shadowed environment. First, terrain-based localization can be readily used to find the vehicle’s absolute longitudinal position within a pre-mapped highway segment – compensating for drift which occurs in dead-reckoning system in long longitudinal stretches of road. Secondly, visual odometry keys upon visual landmarks at a detailed level to correlate position to a (visually) premapped road segment to find vehicle position along the roadway. Both of these preceding techniques rely on foreknowledge of road features – in essence, a feature-enhanced version of a digital map. This becomes feasible in the “connected vehicle” future, in which tomorrow’s vehicles have access to quantities of data orders of magnitude greater than today’s cars, as well as the ability to share data at high data rates. The third technology approach relies on radio frequency (RF) ranging based on DSRC radio technology. In addition to pure RF ranging with no GPS signals, information from RF ranging can be combined with GPS range measurements (which may be inadequate on their own) to generate a useful position. Based on testing and characterization of these technologies individually in a test track environment, Auburn will define a combined Integrated Positioning System (IPS) for degraded GPS environments, which will also incorporate ongoing FHWA EAR work at Auburn in fusion of GPS and on-board sensors. This integrated approach will blend the strengths of each technique for greater robustness and precision overall. This research is expected to be a major step forward towards exceptionally precise and reliable positioning by taking advantage of long-term trends in on-board computing, connected vehicles, and data sharing.

1.1 Sarnoff Corporation Contribution

The scope of Sarnoff’s work under Year One of this project is the evaluation of their Visual Aided Navigation System for providing highly accurate positioning for vehicles. As such there are 3 major tasks:

(1) Evaluate and provide a survey of Sarnoff’s existing Visual Navigation results

(2) Integrate Visual Navigation system on Auburn Engineering’s G35 vehicle test platform and collect test data using the integrated system.

(3) Process and analyze the data from the tests and evaluate the performance and recommend any improvements and optimizations.

1.2 The Pennsylvania State University Contribution

Previous work at Penn State has shown that particle filters can be used for terrain-based localization, and the approach has proven to work offline for defense-grade sensors on specific road sections. The scope of Penn State's contribution to the project involves an extension of the above algorithms. Specifically, Penn State's contribution in the current project consists of the following three tasks:

(1) Developing the proven approach so that it can be used for localization with commercial-grade sensors, rather than defense-grade sensors,

(2) Modifying and optimizing the particle filter algorithm, and exploring alternative approaches, so that localization can take place online (in real-time) rather than offline, and

(3) Modifying and optimizing the algorithms as well as terrain map representation, so that the localization algorithms work over a large network of roads, rather than a small section of a single road alone.

1.3 Kapsch TrafficCom Inc. Contribution

Kapsch will investigate the accuracy of close proximity calculations available from the 5.9 GHz DSRC communications channel. A great deal of information related to positioning can be inferred from the DSRC communications channel. Basic calculations may provide a location region achieved through the channel ranging calculations to more precise lane based proximity determinations through advanced analysis of the communications channel. Kapsch will research a combination of both approaches through available data defined in the IEEE 802.11p standard for 5.9 GHz communication and through scientific Radio Frequency (RF) analysis.

Kapsch will support Auburn for the characterization of the ability to utilize the 5.9 GHz DSRC communication channel for next generation non-GPS localization services. The Received Signal Strength Indication (RSSI) in-conjunction with other aspects of the DSRC communications channel will be analyzed and a method developed for signal ranging. Kapsch does not believe RSSI ranging techniques will fully meet the desired localization needs. Year 2 will yield more advanced algorithms and DSRC equipment capable of providing lane level localization from the DSRC communications channel. This task includes the following sub-tasks:

(1) System Engineering and Deployment of DSRC Infrastructure at the Auburn Test Track

(2) Lab testing of DSRC signal ranging solution

(3) On-site testing of DSRC signal ranging solution

(4) Analysis of DSRC signal ranging test results

2. Current Progress

Auburn's team has been working with each partner in anticipation of the full system integration for Year 2. Each individual system is being identified for its best place on the roof of the new test vehicle, an Infiniti G35. Preliminary work will provide for an easier transition into Year 2. The figures below show the current setup for the hardware on the roof of the vehicle.

The figures below show a computerized model of the layout of various sensors on the roof of the vehicle. The LiDAR, antennas, and mounting bars are shown, along with their dimensions in inches.

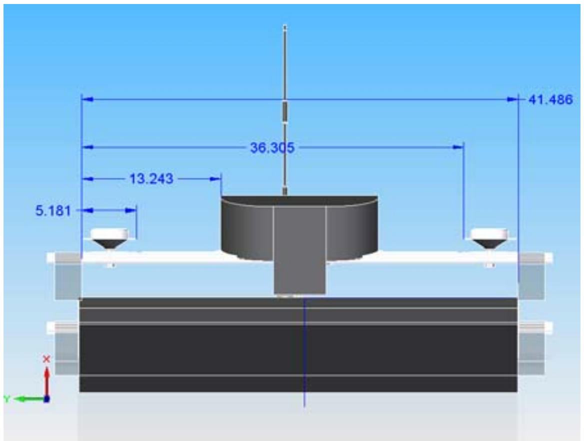


Figure 1: Detailed drawing of roof – front view

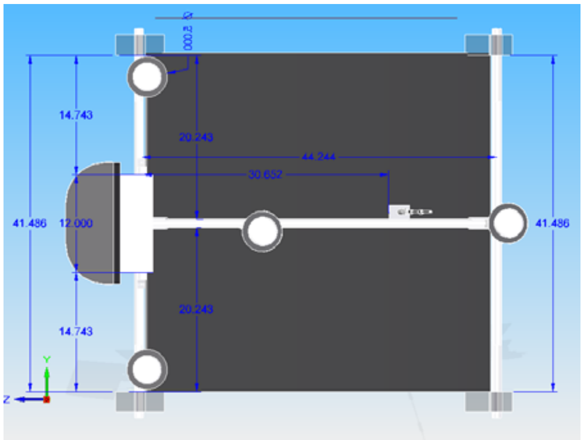


Figure 2: Detailed drawing of roof – top view

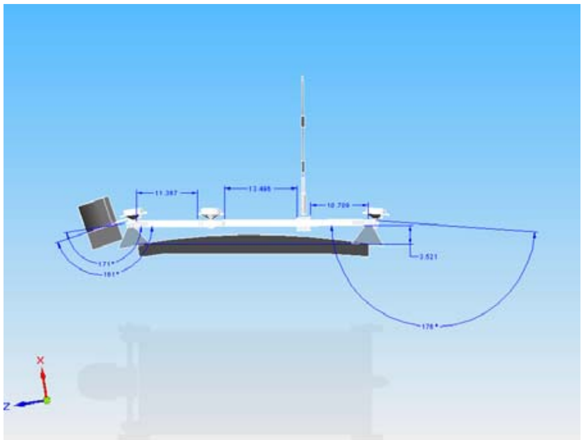


Figure 3: Detailed drawing of roof – side view

2.1 Sarnoff Progress

Sarnoff's plan for integrating a Visual Navigation system on Auburn Engineering's Vehicle Test Platform is as follows:

(1) Design two sensor bars, each holding two cameras and potentially an IMU (low cost MEMS-based)
(2) Collaborate with Auburn Engineering to design mounting points for the sensor bars onto Vehicle Test platform such that it does not interfere with other sensors on the vehicle
(3) Design and build computer data collection system to be installed in vehicle and left at Auburn for duration of tests.

The goal for the design is to create a simple yet robust design. Figure 4 shows the simple bar design that Sarnoff's sensor package will employ. Two cameras and one MEMS-based IMU will be mounted on each bar. Then two bars will be mounted on the front and back T-slot frames on the Auburn Vehicle's roof rack. The bars will be mounted from the bottom of the T-slot frame and spaced such as to avoid interfering with the existing Auburn equipment. Cabling from each bar will follow the same cable routes as the existing equipment.

Figure 4 shows a drawing of a T-slot frame with Thule racks on each side. Two bars extend from the T-slot frame. Between these bars, another bar is shown. Two cameras are present on both ends of the bar, along with an IMU.

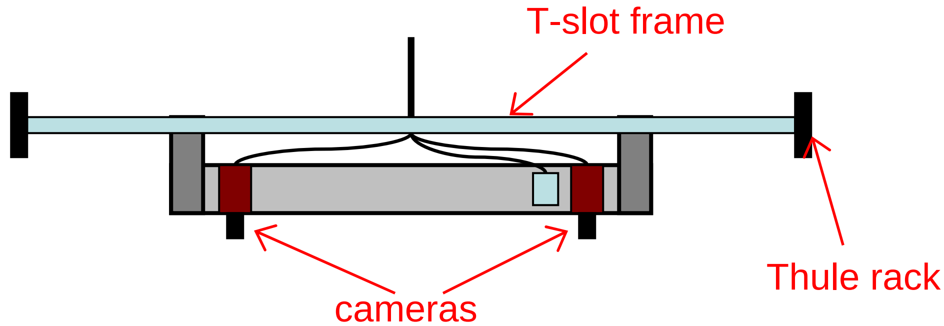


Figure 4: Basic sketch of Sarnoff's Sensor Bar as attached to Auburn's Vehicle roof rack (Figure 5)

The image below is a picture of the actual Thule mount, bar, and an antenna. The mount points are labeled.

Figure 5: Auburn Engineering Vehicle Test Platform roof rack and mount points for Sarnoff Sensor Bar

The drawing below in Figure 6 shows the T-slot with connectors for the mounting bars of the camera. The bars are arranged in an L-shape, with the camera mounted at the tip of the bar.

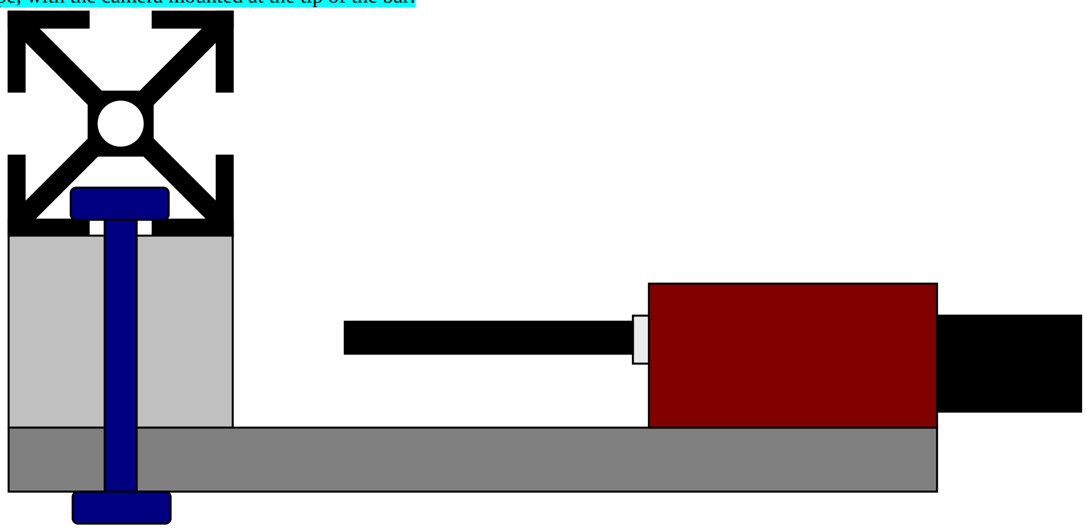


Figure 6: Basic sketch of the attachment points of Sarnoff's Sensor Bar (Figure 4) to Auburn's roof rack (Figure 5)

2.2 Penn State Progress

In the previous quarterly report, the scope of Penn State's contribution to the project was discussed. Specifically, the report mentioned Penn State's goal of building on the current proven terrain-based localization technique (using particle filters) [1] by focusing on the following three tasks:

(1) Developing the proven approach so that it can be used for localization with commercial-grade sensors, rather than defense-grade sensors,

(2) Modifying and optimizing the particle filter algorithm, and exploring alternative approaches, so that localization can take place online (in real-time) rather than offline, and
(3) Modifying and optimizing the algorithms as well as terrain map representation, so that the localization algorithms work over a large network of roads, rather than a small section of a single road alone.

With regards to the tasks mentioned, Penn State has proceeded with Tasks (1) and (2) as per schedule, and Task (3) is scheduled to commence after the completion of the first two tasks. Work completed at Penn State includes sensor noise modeling and characterization, and system architecture design for real-time implementation. Work is currently underway to determine the sensor specification required to achieve a minimum level of localization accuracy, and to create QuaRC/Simulink models for real-time implementation of the localization algorithm. The details of the progress since the previous quarterly report and current and upcoming work are included in the following sections.

2.2.1 Sensor Characterization and Noise Modeling

Task (1) entails the development of the current proven localization approach so that it can be used with commercial-grade sensors. As a first step, the efficacy of the current approach with these sensors needs to be analyzed. In other words, it is desirable to know the minimum localization accuracy achievable with a known commercial-grade sensor with given specifications. Alternatively, the overall problem may also be paraphrased as the determination of the minimum sensor specifications required to achieve a known level of localization accuracy [2].

Penn State has adopted a two-pronged approach in order to establish this link between sensor specifications (or accuracy) and localization accuracy. Specifically, the approach involves:

(1) Developing noise models for sensors. The parameters of the noise models may be varied to simulate data corresponding to different sensor specifications. The minimum sensor specifications that are required to achieve pre-specified localization accuracy may then be identified.
(2) Using actual data collected from commercial-grade sensors. Data is being collected at Auburn with various commercial-grade sensors with known sensor specifications. The localization accuracy achieved can be related to the specifications of the sensors used to collect the data.

Penn State has developed noise models for user-defined sensor specifications using Simulink. Gyro noise components such as angle random walk (ARW) and angular rate random walk (RR) have been modeled as white noise with known variance. Noise components such as bias instability have been approximated as first-order Gauss-Markov processes [3][4]. These models can be used to simulate sensor data which can then be used in the localization algorithm determine the achievable localization accuracy. Penn

State has also developed MATLAB scripts to characterize existing commercial-grade sensors using methods found in the literature [4][5][6].

Penn State has used a synthesis-analysis approach to validate the noise models and sensor characterization scripts. Specifically, Simulink noise models have been used to simulate noisy data with known parameters, and the MATLAB scripts have been used to recover the input sensor specifications from the noisy data. Sensor data was synthesized using an angle random walk noise model with known variance of 0.1^2 $(deg/sec)^2$. The Allan variance analysis (Figure 7) was then performed, and sensor specifications recovered from analysis indicate the noise variance to be 0.091^2 $(deg/sec)^2$.

The graph below shows the Root Allen Variance and the correlation time. The Root Allen variance begins at 0.1 deg/sec at .001 seconds and decreases linearly on a log-log scale to .0001 deg/sec with a correlation time of almost 1000 seconds.

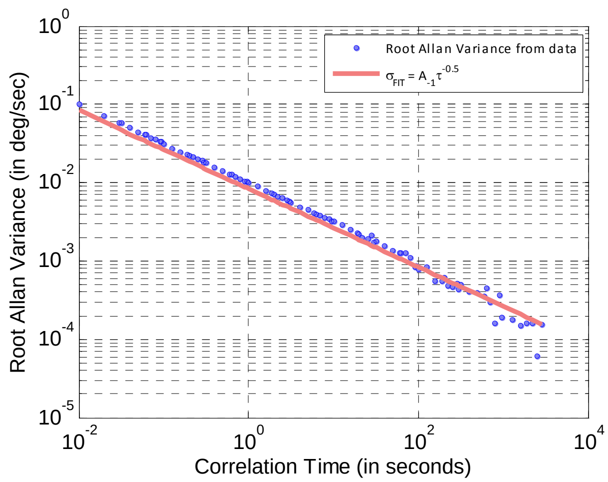
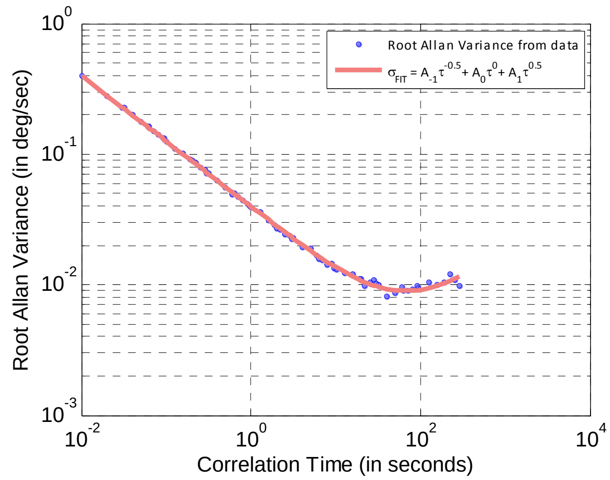


Figure 7: Sensor specification recovered from Allan variance analysis: $\sigma_{ARW} = 0.091\frac{deg}{sec}$.

True specification of noise was $\sigma_{ARW} = 0.1\frac{deg}{sec}$

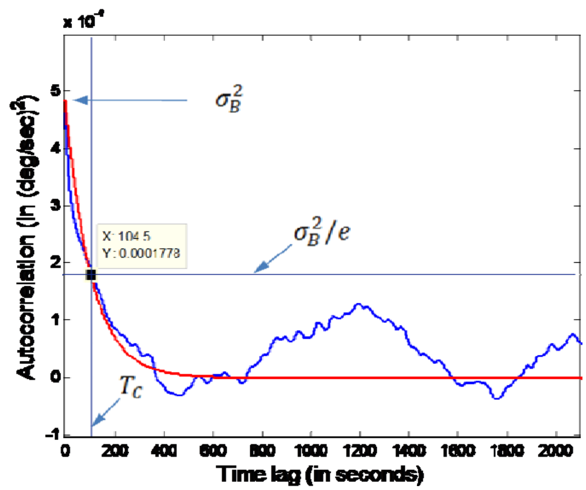
Additional noise sources such as bias instability were also introduced into the Simulink model. Sensor data was synthesized using both angle random walk and bias instability noise models. For this example simulation, the ARW noise has the specifications: standard deviation, $\sigma_{ARW} = 0.4\frac{deg}{sec}$, and the bias instability noise has the specifications: standard deviation, $\sigma_B = 0.02\frac{deg}{sec}$ and correlation time, $T_C = 150\ sec$. Angle random walk noise typically has a higher variance as compared to bias instability noise and this is reflected in the choice of sensor noise variances. Figure 8(a) indicates the Allan variance analysis for the simulated data. As mentioned in the previous quarterly report [2], bias instability is essentially flicker noise and is approximated as a first order Gauss-Markov, which is exponentially correlated. Consequently, noise models used to fit a curve to the root Allan variance include exponentially correlated noise. An alternative technique for determining bias instability uses signal autocorrelation, as described in [5][6]**.** Autocorrelation techniques are used to establish an upper bound for the bias instability noise characteristics. Figure 8(b) indicates the autocorrelation analysis performed on filtered simulated data for recovering the bias instability noise characteristics.

The graph below shows the Root Allan variance analysis once more. In this graph, the Root Allan variance decreases linearly on a log-log scale to about .01 deg/sec at 100 second correlation time and then arcs upward to create a hockey stick graph.



(a) Sensor specification recovered from Allan variance analysis $\hat{\sigma}_{ARW} = 0.398\frac{deg}{sec}$

The graph below shows the Autocorrelation in $(deg/sec)^2$. The autocorrelation converges to 0 in about 400 seconds.



(b) Sensor specification recovered from Allan variance analysis: $\hat{\sigma}_B = 0.022\frac{deg}{sec}, T_c = 150\ s$

Figure 8: Allan variance and autocorrelation analysis for noise simulated using the following specifications: $\sigma_{ARW} = 0.4\frac{deg}{sec}, \sigma_B = 0.02\frac{deg}{sec},$ and $T_c = 150\ s$

Penn State also performed sensor characterization for the Crossbow IMU 440 using data collected at Auburn. The sensor specifications obtained from the analysis are included in Table 1. Figure 9 depicts the Allan variance analysis plot for the y-axis gyro of the Crossbow IMU 440.

Table 1: Sensor specifications obtained from Allan variance analysis of Crossbow IMU 440

Y-axis gyro noise specification	Value
σ_{ARW}	0.038 deg/sec
σ_B	0.0057 deg/sec
T_C	357 seconds

Figure 9 shows the Root Allan Variance. In this graph, the Root Allan Variance begins at .1 deg/sec and decreases in a 2nd order parabolic fit on a log –log scale to a vertex at almost .001 deg/sec at 100 second correlation time.

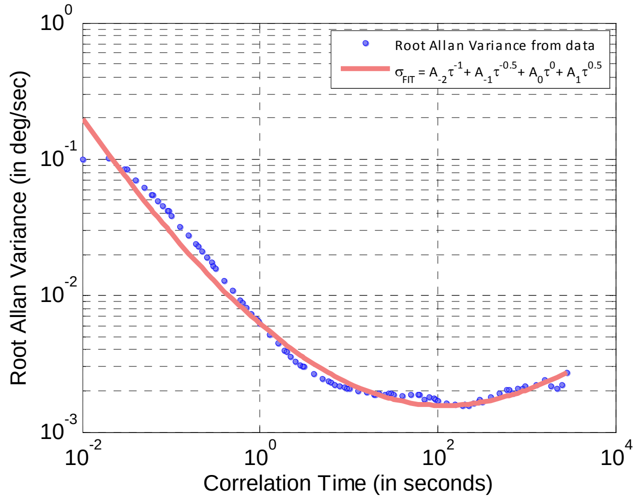


Figure 9: Allan variance analysis plot for data collected from Crossbow IMU 440

In summary, Penn State now has the capability to generate simulated data for any desired sensor specifications. As a result, any desired simulated sensor accuracy can be achieved. Further, Penn State has also developed the capability to recover sensor characteristics from data collected using actual sensors. Together these will enable Penn State to conclusively establish a link between sensor specifications and localization accuracy. Specifically, these analyses will accomplish the following goals:

(1) Analyzing localization accuracy achieved with an algorithm, given data corrupted by sensors with different specifications,

(2) Comparing algorithms by analyzing their localization accuracy given the same set of inputs and sensor specifications, and

(3) Allowing the development of sensors with specifications that meet a certain pre-specified localization accuracy (with a benchmarked algorithm)

2.2.2 System Architecture for real-time implementation

Task (2) entails the development of a real-time implementation of the localization algorithm. The localization algorithm is intended to provide accurate position estimates during periods and/or regions with weak or absent GPS signals. Penn State has developed the system architecture for implementing such an algorithm that describes the flow of information across various subsystems such as the terrain database, the estimation algorithm etc. Figure 10 depicts the designed system architecture.

The system has been divided into four modular subsystems, allowing separation of functionality, which further facilitates individual development and testing. The four subsystems or layers in the system architecture are as follows:

(1) Supervisory layer
(2) Algorithmic layer
(3) Sensing layer, and
(4) Database layer

A fifth layer that exists external to the system is the IPS (integrated Positioning System) layer that controls when and how the terrain based localization algorithm is activated. The functions and details of each of these layers are explained in detail in the following subsections.

The system architecture block diagram is shown in Figure 10. The environment is shown as an input to the system on the left. The data is moved to the algorithm supervisor in the IPS layer, which is then used in constructing the estimator and initialization module. Various exception handling and buffers are present throughout the architecture. Information is also then sent into both an on-board and off-site database.

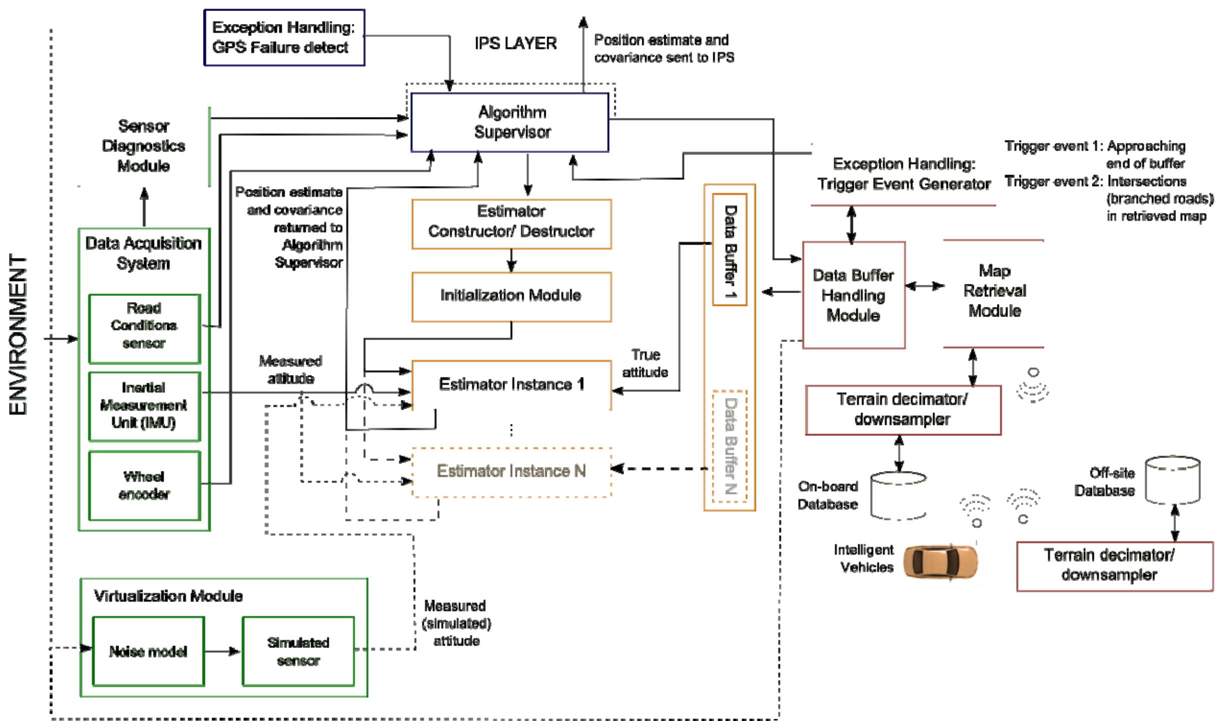


Figure 10: System architecture detailing system setup and data flow for real-time implementation

2.2.3 Supervisory Layer

The function of the Supervisory layer is to maintain communication with the Integrated Positioning System central supervisor. The major functions of the Supervisory layer include receiving initialization conditions for the estimation algorithm, and transmitting current position estimates and covariance matrices to the IPS layer for data fusion.

Secondary functions of the Supervisory layer include correctly initializing the estimation algorithm and responding to internally generated interrupts such as:

(a) Interrupts related to sensor diagnostics indicating failed sensors. In this scenario, the supervisory layer is expected to discontinue sending position estimates to the IPS.

Interrupts related to arrival of the vehicle at intersections. In this scenario, the Supervisory layer is expected to command the construction new instances of estimators to handle branched roads till the estimation algorithm converges to the correct position estimate. The Supervisory layer is also expected to command the destruction of estimators when it becomes evident that they are not tracking the true vehicle position.

The supervisory layer is shown in Figure 11. Various inputs, such as sensor diagnostics, exception handling, wheel encoder data, position estimates, and trigger events, are shown as inputs. Outputs include the estimator constructor/destructor commands, position estimate and covariance, and position information for the database map retrieval commands.

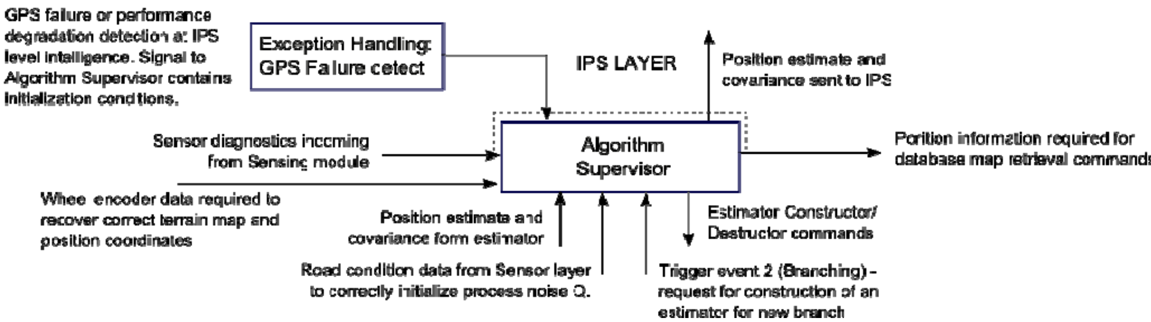


Figure 11: The Supervisory Layer

2.2.4 Algorithmic Layer

The primary function of the Algorithmic layer is to perform the actual state estimation using prerecorded and measured attitude data. Both particle filter and unscented Kalman filters have been shown to work for local tracking of vehicles [1]. The Algorithmic layer receives measurement information from the Sensing layer, true terrain data from the Database layer, and commands for construction and destruction of estimators from the Supervisory layer. It sends the position estimates and covariance matrices to the Supervisory layer. When multiple estimators exist, the Algorithmic layer also maintains the data buffers for each estimator instance. Figure 12 depicts the functions and data flow in the Algorithmic layer.

Figure 12 shows the Algorithmic Layer. This stage takes commands from the Algorithm Supervisor for constructing / destroying estimator instances, initializes modules, and creates one or more estimator instances. The true attitude is used in the data buffer from the database layer for the estimator instances as well as the measured attitude values from the sensor layer.

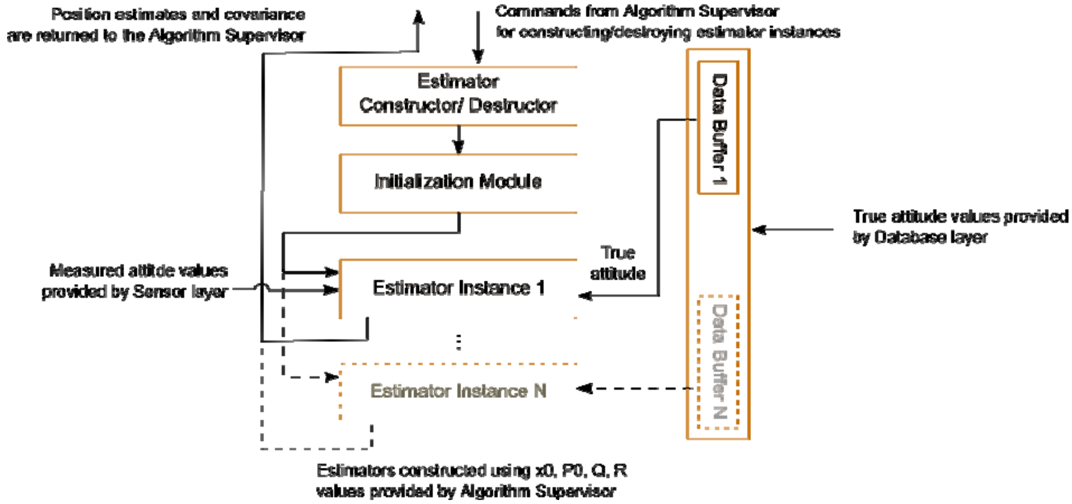


Figure 12: The Algorithmic Layer

2.2.5 Sensing Layer

The Sensing layer performs the functions of acquiring data from the environment, sending the data to the Algorithmic layer for processing, and monitoring sensor health. The Sensor layer consists primarily of three types of sensors – the IMU for terrain attitude measurement, wheel encoders for odometry, and in the future may contain some form of road or weather monitoring sensors in order to correctly initialize the process noise covariance, Q. The Sensing layer also contains the Virtualization module, which will be utilized to test the estimation algorithm with simulated sensor data. Figure 13 depicts the Sensing layer.

Figure 13 shows the Sensing Layer. Information from the environment is obtained through wheel encoders, IMU's, road conditions sensors in order to determine if the sensors degrade beyond acceptable limits.

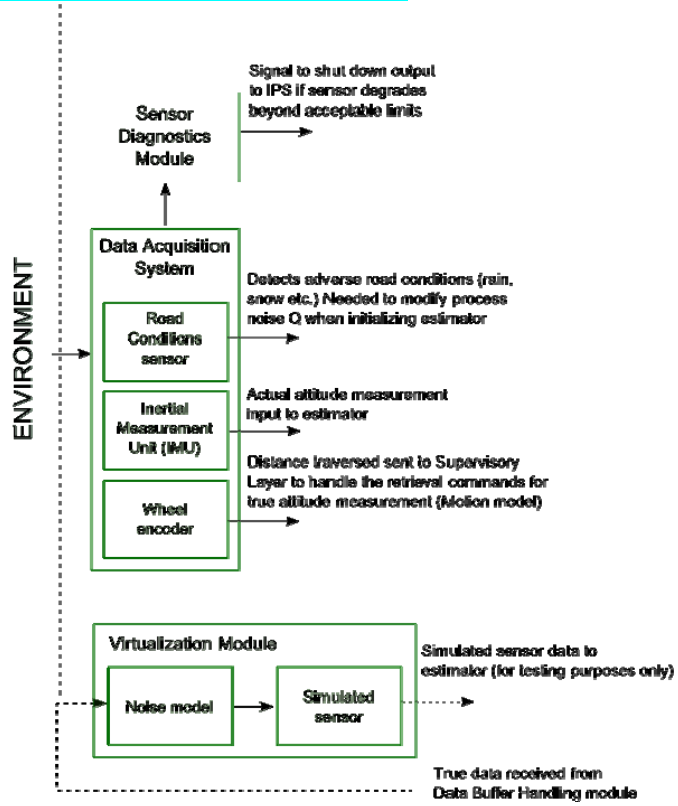


Figure 13: The Sensing Layer

2.2.6 Database Layer

The primary function of the Database layer is to store, retrieve and output terrain map data for the Algorithmic layer. The layer retrieves maps that may be stored on-board or at an off-site database, or may even be transferred from vehicle to vehicle. The Database layer also handles exception events such as arrival of the vehicle at an intersection, or retrieval of data for successive road segments. The layer uses the commands received from the Supervisory layer to retrieve data for the next road segment. Figure 14 depicts the Database layer.

The Database Layer takes information from the Supervisory Layer to determine if a trigger event is needed in the case of an intersection or the end of the buffer or to send data to the Algorithmic layer. Information form an on-board database, off-site database, or another vehicle helps reduce overhead by transmitting maps at a resolution appropriate for on-board sensing equipment.

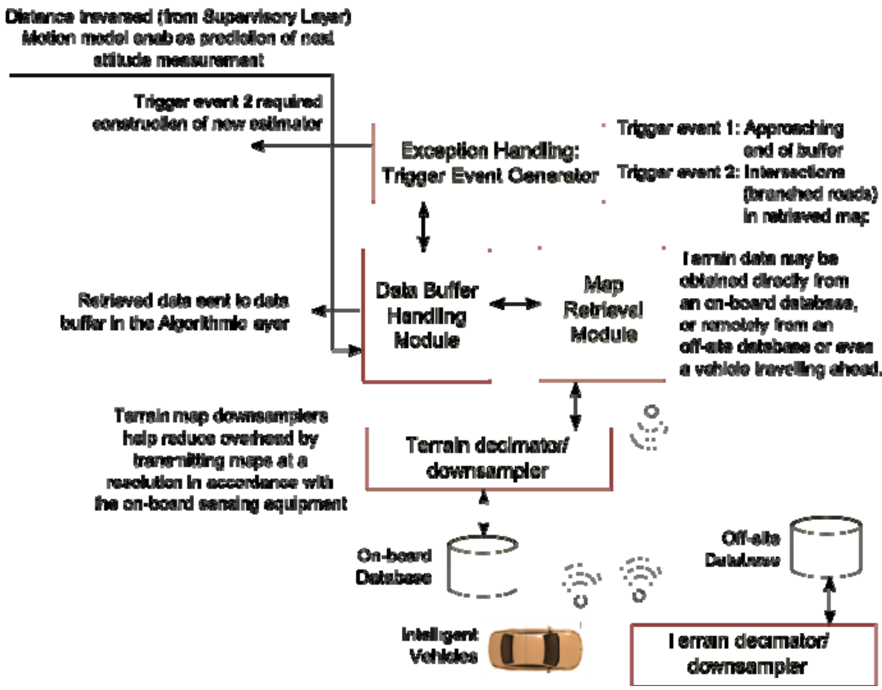


Figure 14: The Database Layer

2.3 Kapsch TrafficCom Inc. Progress

This section summarizes the work activities accomplished by Kapsch TrafficCom Inc. in support of Year 1 Task 5 activities during the reporting period.

(1) Kapsch and Auburn University finalized the contract in early February 2010 after the Auburn University contract was reviewed by the legal department of Kapsch TrafficCom.

(2) Kapsch TrafficCom submitted necessary information to be added to the Auburn University preferred vendor list.

(3) Auburn University issued a purchase order to procure equipment required to fulfill Task 5 Year 1 research activities.

(4) Kapsch preparing hardware and software according to the purchase order. The hardware units required for the initial ranging evaluation include Multiband Configuration Networking Unit (MCNU). These units are designed as a multi-purpose communication platform that provides 5.9GHz DSRC capabilities. Two MCNU platforms were update with the latest software which included an updated version of the Kapsch TrafficCom 5.9GHz WAVE DSRC software stack and test applications. A test application was included into MCNU software image that can be used to conduct a communication testing between the two units. In addition to the MCNU units, Kapsch procured and prepared necessary RF and GPS antennas,

power cables, mounting hardware and other miscellaneous components. The two MCNU units were tested before shipment to Auburn.

(5) The purchase order was fulfilled in March when the equipment was shipped to Auburn University.

(6) In February 2010, Kapsch presented at the Automotive panel. Kapsch discussed 5.9GHz DSRC technology and its capabilities to fulfill the research goals of the Task 5. Kapsch scope of the task and capabilities of the DSRC hardware platform that will be used in Year 1 and Year 2. Specifically, Year 2 testing will utilize the Next-Generation Roadside Transceiver which will provide high-accuracy vehicle localization in the lane without GPS. The automotive panel showed considerable interest to review the results obtained from the Next Generation transceiver. Testing of the next-generation transceiver is planned for the Year 2 of the project.

3. Future Work

Auburn University will continue to work with each partner to equip the test vehicle for testing.

3.1 Sarnoff Future Work

Future work for Sarnoff's portion of the project involves the integration and testing of the system at Auburn University.

(1) Build and calibrate individual sensor bars
(2) Create software testing system and procedures
(3) Integrate, calibrate, and test whole system onto Auburn's Vehicle Test Platform

Each sensor bar will consist of 2x AlliedVision Marlin F-033B cameras and a CloudCap Crista IMU. The stereo baseline will be about 40cm. Firewire, trigger, power and serial cables will be bundled from each bar and routed inside the vehicle where the computer and trigger device will be located. Data will be able to be recorded or processed live on a Windows PC (small form factor or laptop).

3.2 Penn State Future Work

3.2.1 Link Between Sensor Specifications and Localization Accuracy

Penn State is in the midst of analyzing the relation between sensor specifications and localization accuracy. Work is currently underway to corrupt true attitude data using sensor noise models and using the corrupted attitude data as input to the proven particle filter algorithm. This process will allow Penn State to clearly identify the impact of individual noise sources and overall sensor specifications on localization accuracy.

3.2.2 Real-time Implementation of Unscented Kalman Filter

Penn State has simultaneously started developing Simulink models using Unscented Kalman Filters as the algorithm of choice for localization. UKFs have a lower computational overhead as compared to particle filters. Further, stability of particle filters cannot always be assured, which makes them a less-than-desirable choice for commercial implementation. Additionally, data is currently being collected by our colleagues at Auburn University to generate a data set for testing the estimation algorithms being developed. The data is being collected across various road surfaces (highway, city and rural) to analyze the specific impact of road surface on localization accuracy.

3.2.3 Future Plans

Penn State's plans for the near future involve completion of the real-time implementation of the terrain-based localization algorithms in a Simulink/QuaRC environment. Since the overall objective of the project is to develop terrain-based localization algorithms which function over a large road network and are optimized for induction into real-time systems, Penn State also plans to collect terrain attitude data for a local road network. The collected data will first be used for offline real-time testing of the localization algorithms followed by an online real-time testing later in June.

The current localization algorithm relies on initialization via an external source. In view of the global localization problem, Penn State is currently examining feature-based localization techniques [7] in order to achieve a truly GPS-free localization algorithm. The terrain data is being used to develop feature trees, which may allow a more compact representation of terrain, while simultaneously reducing the computational load associated with particle filters. Considerable progress has been made along the lines of generating relevant feature vectors using wavelet transforms. Penn State now plans to analyze the feasibility of applying the feature-based method to the global localization problem in real-time.

3.3 Kapsch Future Work

This section summarizes the anticipated project tasks for the Kapsch team during the following quarter.

(1) Completing a Non-disclosure Agreement (NDA) between Kapsch and Auburn University. The NDA is required to allow Kapsch to share proprietary information regarding the Kapsch new localization technology incorporated into the Next Generation Roadside Transceiver.

(2) Develop testing plan for the phase 1 of the project.

(3) Develop deployment plan for 5.9 DSRC hardware at the Auburn Test Track.

(4) Deploy 5.9 DSRC hardware and conduct on-site testing at the Auburn Test Track.

(5) Design and develop the software interface required for DSRC ranging experiments at the Auburn system.

References

[1] Dean, A.; Terrain-based Road Vehicle Localization using Attitude Measurements, Ph.D. Dissertation, The Pennsylvania State University, 2008

[2] Next Generation Vehicle Positioning Techniques for GPS-Degraded Environments to Support Vehicle Safety and Automation Systems, FHWA BAA DTFH61-09-R-00004, Exploratory Advanced research Program, Quarterly Report 1, 2009

[3] Gelb, A. Editor, Applied optimal Estimation, M.I.T. Press, Cambridge, Mass., 1974.

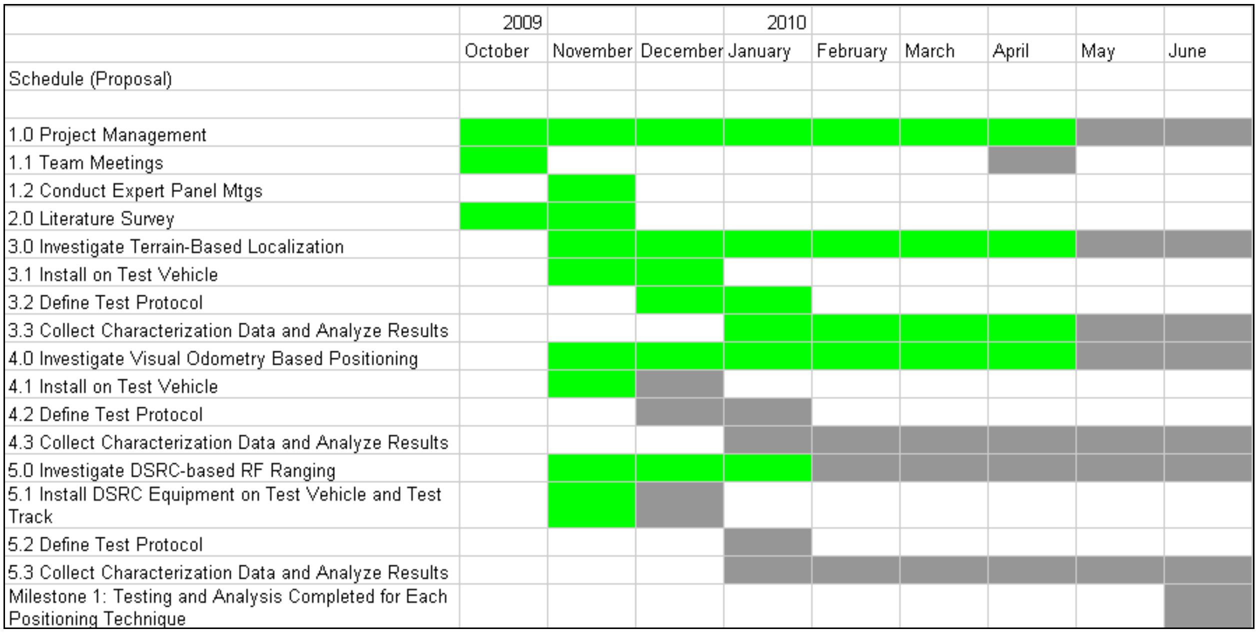
[4] Han, S., Wang, J., and Knight, N.; Using Allan Variance to determine the Calibration Model of Inertial Sensors for GPS/INS Integration, *Proceedings of the 6th International Symposium on Mobile Mapping Technology*, Sao Paulo, Brazil, 2009.

[5] Xing, Z., and Gebre-Egziabher, D.; Modeling and Bounding Low Cost Inertial Sensors, *IEEE/ION Position, Location and Naviagtion Symposium*, 2008.

[6] Wall, J.; A Study of the Effect of Stochastic Inertial Sensor Errors in Dead-Reckoning Navigation, M.S. Thesis, Auburn University, 2007

[7] Ferrari, V., Tuytelaars, T., and Van Gool, L.; Object Detection by Contour Segment Networks, *Proceedings of the European Conference on Computer Vision*, 2006

Gantt Chart


2009
2010
October
November
December
January
February
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Schedule (Proposal)
1.0 Project Management
1.1 Team Meetings
1.2 Conduct Expert Panel Mtgs
2.0 Literature Survey
3.0 Investigate Terrain-Based Localization
3.1 Install on Test Vehicle
3.2 Define Test Protocol
3.3 Collect Characterization Data and Analyze Results
4.0 Investigate Visual Odometry Based Positioning
4.1 Install on Test Vehicle
4.2 Define Test Protocol
4.3 Collect Characterization Data and Analyze Results
5.0 Investigate DSRC-based RF Ranging
5.1 Install DSRC Equipment on Test Vehicle and Test Track
5.2 Define Test Protocol
5.3 Collect Characterization Data and Analyze Results
Milestone 1: Testing and Analysis Completed for Each Positioning Technique