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

SRI (formerly Sarnoff) Corporation

The Pennsylvania State University

Kapsch TrafficCom Inc.

NAVTEQ North America LLC

Quarterly Report 5

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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

For sake of clarity and coherence, the scope of Penn State's contribution to the project, as discussed in previous quarterly reports, is reproduced here. The primary objectives under Penn State's purview are:

(1) Developing the proven particle filter 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.

Following up from previous quarterly reports, as part of Task (2), Penn State has completed the offline testing of the Simulink model developed for real-time implementation. The model is now being incorporated into the QuaRC/Simulink architecture for field testing. Work on Task (3) is progressing with review of prevalent multiple model estimation techniques which will be used for vehicle position tracking on a large road network.

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

2.1 SRI Progress

2.1.1 Visual Navigation Sensor Package and Data Collection

The sensor package for visual navigation consists of cameras and IMU mounted on the vehicle roof rack, described in a previous report.

SRI Sarnoff visited Auburn University on 1/16/2011 - 1/18/2011 for data collection and system tests. The sensor system installed at Auburn University on 10/3/2010 was found to be breached and have water damage. The rear cameras were non-responsive and the glass lens covers were fogged with internal condensation for both front and rear cameras. Both camera boxes were resealed with external application of RTV adhesive, and data was collected on the Auburn test track in rainy conditions.

The camera boxes and breakout box were shipped to SRI Princeton, where it was found that the sealant used to secure the glass lens covers had failed, letting rainwater into the boxes. The GigE network hub and one camera were damaged. The front camera box will be returned to Auburn for continued testing and inclusion in the integrated positioning system.

2.1.2 Visual Navigation System and Software

During the 01/2011 trip to Auburn University, full system functionality was demonstrated including successful live interface with the Auburn vehicle computer.

- **GPS NMEA messages**: The SRI laptop was connected to the vehicle GPS receiver via serial cable and GPS data was streamed to the live visual odometry software.
- **Visual Odometry Poses output over TCP/IP:** The 6 degree-of-freedom position and bearing estimates were successfully streamed to the Auburn vehicle computer over TCP/IP Ethernet connection.

Progress has also been made at SRI on various parts of the visual navigation system.

- **Diagonal pose covariances** are now being calculated by the SRI visual odometry software. This is a necessary component for the integrated positioning system.
- **Extended Kalman Filter:** An extended Kalman filter is used to fuse the measurements from visual feature tracking and a low-cost IMU. Two different formulations for the EKF have been developed at SRI, and both were evaluated using data collected in October, 2010. The first formulation is a velocity process model which specifies an explicit dynamic motion model for a given sensor platform, or assumes a constant velocity process if no dynamic model is given. The second filter representation uses an *error-state formulation*, where the filter dynamics follow from IMU error propagation equations, which evolve slowly over time and are therefore more amenable to linearization. The measurements propagated to the filter consist of the differences between the inertial navigation

solution as obtained by solving the IMU mechanization equations and the external source data, which in our case is the relative pose information provided by visual odometry through feature tracking. In general, the second filter representation has proven more accurate for platforms including human-mounted systems and rough-terrain robots. However, the performance on the Auburn track data was worse with the error-state formulation and showed a higher accuracy from the constant velocity formulation. This is not surprising, since the vehicle-mounted system actually does maintain a smooth velocity over short time frames, especially compared with a helmet-mounted system.

2.1.3 Visual Navigation Data Analysis

Data was collected at the Auburn test track in rainy conditions on 01/17/2011, and analysis of the data is ongoing. RTK position measurements were recorded during these data collects. The data was collected from the front stereo cameras at 30Hz, from the Cloudcap Crista IMU at 100Hz, and from the Septentrio GPS at 10Hz. The rain caused significant blurring in the image, thus decreasing the number of tracked features per frame, but this did not cause visual navigation to fail.

Image samples from front stereo pair. Rain caused image blur and specularities. Fogging of right image was caused by condensation between camera CCD and lens.

Figure 1: Rainy images (stereo) using SRI's Visodo system on the on ramp of the NCAT test track

Figure 2: Rainy images (stereo) using SRI's Visodo system on the NCAT test track

Feature tracking on four rand-blurred image sampled. Even on the most affected images, there are enough features.

Figure 3: Images of feature tracking with rain data.

The figure below shows Visodo's position estimates during two laps around the track. The drift is very evident by the paper clip like shape of the position estimates.

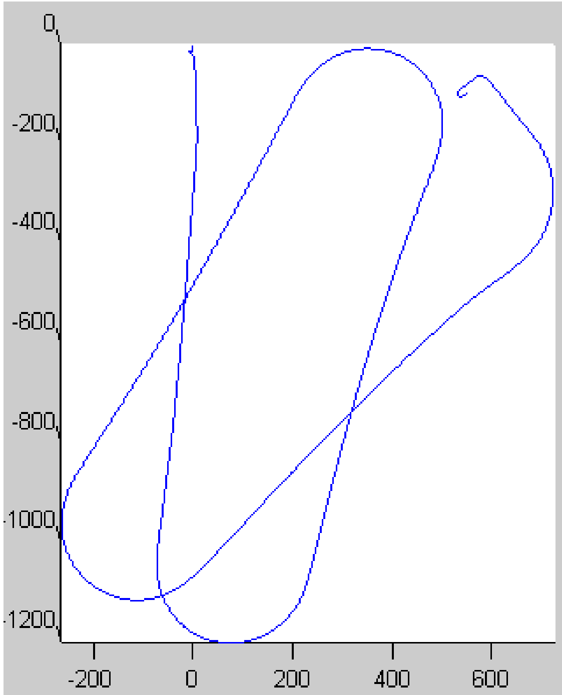

Figure 4: Visual Odometry with no GPS updates (local coordinate frame) (meters)

The figure below shows visual odometry with GPS input but with simulated outages to show the affect of GPS loss on the system. The system drifts slightly and is most apparent on the straightaways.

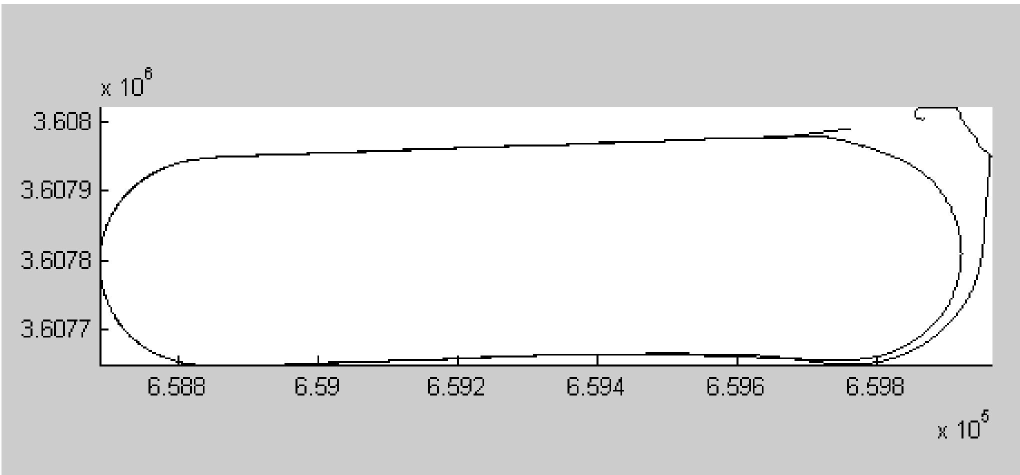

Figure 5: Visual Odometry with GPS input with simulated outages (30%, in 3 chunks) (meters)

The figure below shows visual odometry trajectory with GPS input and no outages. The position estimates line up well with the track's shape.

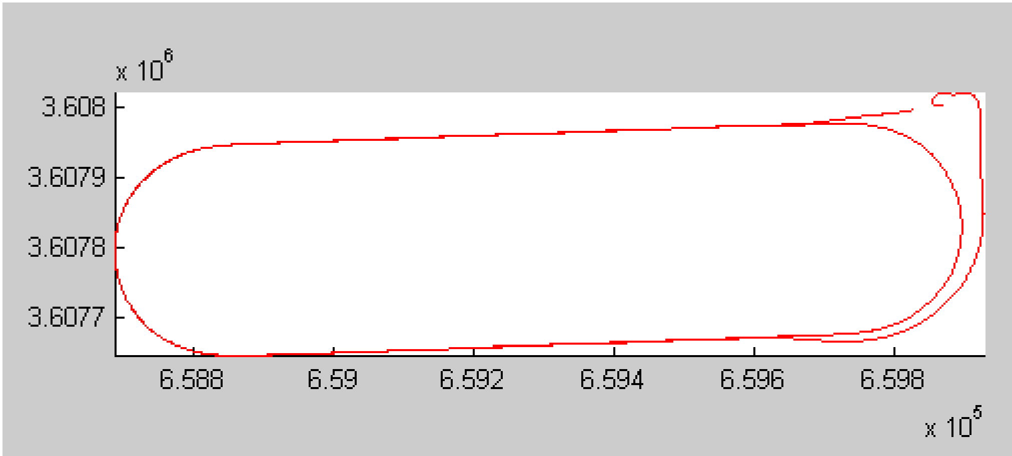

Figure 6: Visual odometry trajectory with GPS input (UTM coordinate frame) (meters)

2.2 Penn State Progress

Following up from previous quarterly reports, Penn State has successfully conducted the initial field tests of the terrain-based localization algorithm at Penn State. The algorithm performed satisfactorily with tracking being maintained at meter level accuracy during the test run. Work is currently underway to create an appropriate terrain map representation to increase the algorithm's functionality to encompass an entire road network. The details of the progress since the previous quarterly report and current and upcoming work are included in the following sections.

2.2.1 Real Time Implementation

Task (2) entails the development of a real-time implementation of the localization algorithm. At the time of submission of the previous quarterly report, the Simulink model for the algorithm had been tested in an offline environment. During the last quarter, the algorithm was implemented in real-time and was tested at the Pennsylvania Transportation Institute's test track. The test vehicle was instrumented to collect odometric data through encoders mounted on the wheels, and vehicle attitude data through the HG1700 tactical grade IMU. Since one of the aims of the project was to demonstrate the ability of the algorithm to work with low-cost commercial grade sensors, the attitude data acquired from the HG1700 IMU was corrupted using a noise model representative of an XBOW 440 IMU available at Auburn University. The process of determining the noise model for the XBOW 440 is documented in the quarterly report submitted in April 2010. The test vehicle and instrumentation setup are shown in Figure 8 and Figure 7.

Figure 8 shows the Penn State test vehicle equipped with a GPS receiver on the roof and an encoder mounted on the wheel. Figure 7 shows the instrumentation setup including the HG1700 tactical grade IMU.

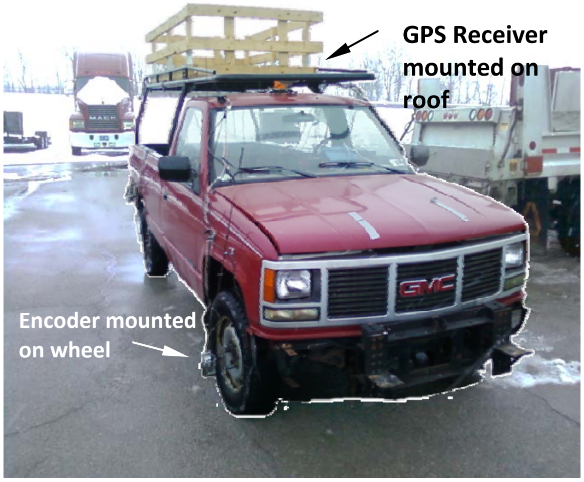

Figure 8: Test vehicle

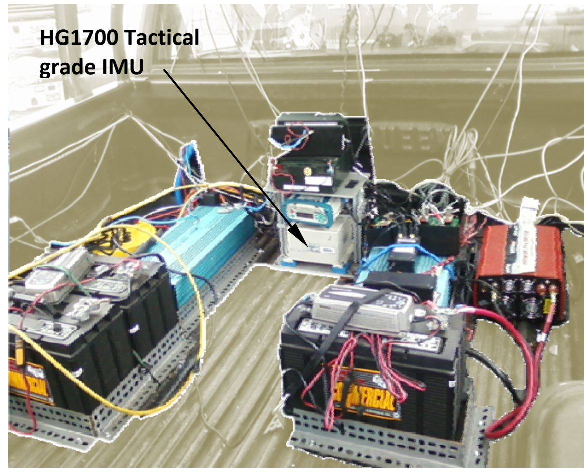

Figure 7: Instrumentation setup

At this point, we would like to emphasize that the simulated attitude data received from the simulated XBOW varies markedly from the 'true' attitude stored in the terrain map. Here, the 'true' attitude (or in this case 'true' pitch) is defined as the attitude measured using the tactical-grade HG1700 IMU system. During the test run, the pitch measured from the noisy simulated XBOW 440 IMU drifted from the 'true' pitch, with the error in measurement reaching to values as large as 2 degrees. However, the algorithm continued to track the vehicle position with satisfactory performance. The results of the real-time tracking are included in Figure 9. In the test run, during which the vehicle traveled approximately 1 km, tracking accuracy hovered in the meter level range.

Figure 9 shows the real-time tracking error. The error begins at 4 meters, peaks at 6 meters, then falls to 0 meters at 20 seconds into the run. The error immediately increases to 3 meters until it falls back to 0 meters at 40 seconds. The error thenremains at 1 meter until the end of the run.

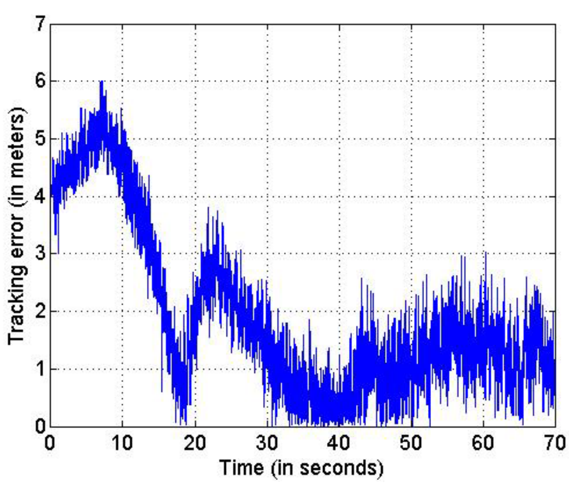

Figure 9: Real-time tracking error. Vehicle tracking is maintained at meter level accuracy using a simulated 'noisy' XBOW 440 IMU

2.3 Kapsch TrafficCom Inc. Progress

The figure below shows the timeline for time of flight ranging. One vehicle sends a request for acknowledgement. The base radio receives the acknowledgement and sends it back. In addition to the times of flight for sending and receiving, the receive request and send acknowledgement times are included.

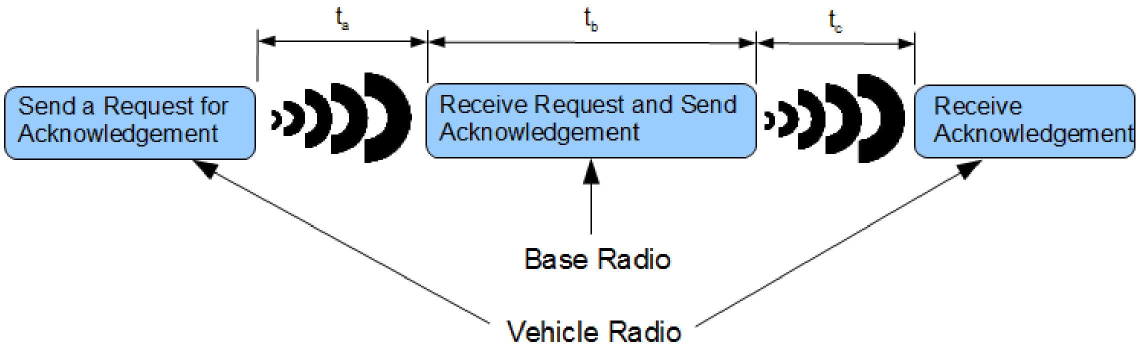

Figure 10: Timeline for time of flight ranging

2.3.1 DSRC Ranging Timeline

Figure 10 shows the timeline for time of flight ranging using DSRC radios. Since the clocks on the radios are not synced, a two-way time of flight method will be used to estimate range. The vehicle's radio will measure the overall time of flight and sends a message requesting acknowledgement from a base radio. The vehicle's radio must also start a precise timer when the message is sent. Ideally, this time will start as soon as the message starts to propagate from the radio's antenna. The base radio will receive the request and then send an acknowledgement. The turnaround time (t_b), or the time it takes the base radio to receive the message and send the acknowledgment, must be known in order to compute the range between the radios. Once the vehicle's radio receives the acknowledgement, it will stop the timer. Ideally the timer will stop as soon as the vehicle's antenna receives the message.

$$t_{total} = t_a + t_b + t_c$$

The vehicle's receiver measures total time of flight. The total time is the sum of the flight time from the vehicle to the base (t_a), the turnaround time at the base station (t_b), and the flight time from the base back to the vehicle (t_c). If the turnaround time (t_b) is known, the equation below can be used to estimate the range (r) between the vehicle's radio antenna and the base radio's antenna. c is the speed of light.

$$r = c\frac{(t_{total} - t_b)}{(2)}$$

There are several considerations that must be investigated when using the flight time method for ranging. Most of these concerns center on the necessary precision of the t_b and t_{total} times. Since these times are multiplied by a large number (the speed of light), an inaccuracy in the times will result in a large range estimate. An error of one microsecond (1/100000 of a second) will result in a 300 meter error in range. The signal traveling at the speed of light will travel approximately one foot every nanosecond; therefore, the total flight time (t_{total}) and the turnaround time (t_b) must be known to at least to the nanosecond to result in a range accuracy of one foot.

The DSRC radios have an onboard 1GHz processor. Theoretically, the processor should be able to measure time to the nanosecond because the cycle time of the processor is 1 nanosecond. Another issue is error in the total time due to the timer not starting and stopping precisely when the message is being sent/received at the antenna, and it may be necessary to estimate the time from when the time of flight timer is started and when the request message starts to propagate from the antenna. Similarly, it may also be necessary to estimate the time difference from when the acknowledgement is received at the antenna and when the time of flight timer is stopped. Since these time differences are based on the receiver's hardware, they should be constant.

The time it takes the base radio to receive the request and send the acknowledgement must also be known to the nanosecond in order to have an accurate range estimate. One method of determining the turnaround time is setting up the antennas at a known range and measure the time of flight. The known range can be used to estimate the turnaround time. The estimated turnaround time can be used as a constant. This method will require that the turnaround time be constant on the nanosecond level. Due to software processes involved in the turnaround time, it is unlikely that this time will be constant to the nanosecond. Another method of determining the turnaround time could involve the base radio estimating the turnaround time using its own timer. This time could then be sent in the acknowledgement or another message that is sent right after the acknowledgement. The vehicle's receiver will then have an estimated turnaround time (accurate to the nanosecond) to use in the range estimation.

Another issue will be what value is use for the speed of light. The speed of light is 299,792,458 meters per second in a vacuum; however, the speed of light is slowed when traveling through a medium like air. The refractive index of a medium is the ratio of the speed of light trough the medium and to the speed of light in a vacuum. There are methods on determining the correction to the speed of light through air based on current properties of the air like temperature and pressure.

2.4 Auburn University Progress

2.4.1 MOOS

A significant part of a multisensor system is the data collection of each of the individual sensors and the ability to quickly change the system for various tests. Auburn University has chosen the MOOS architecture for data recording and playback. MOOS is a cross platform software architecture written in C++ which uses the well known Boost C++ libraries. It uses TCP/IP packets for sending data between the client (sensors) and the MOOS database. The MOOS database is the hub of the MOOS architecture, and all data is timestamped and recorded in the database.

The figure below shows a Graphical User Interface for the data being saved in the database. The values corresponding to each variable are the most recent values obtained from the sensor. The red values show that the variable value had recently changed.

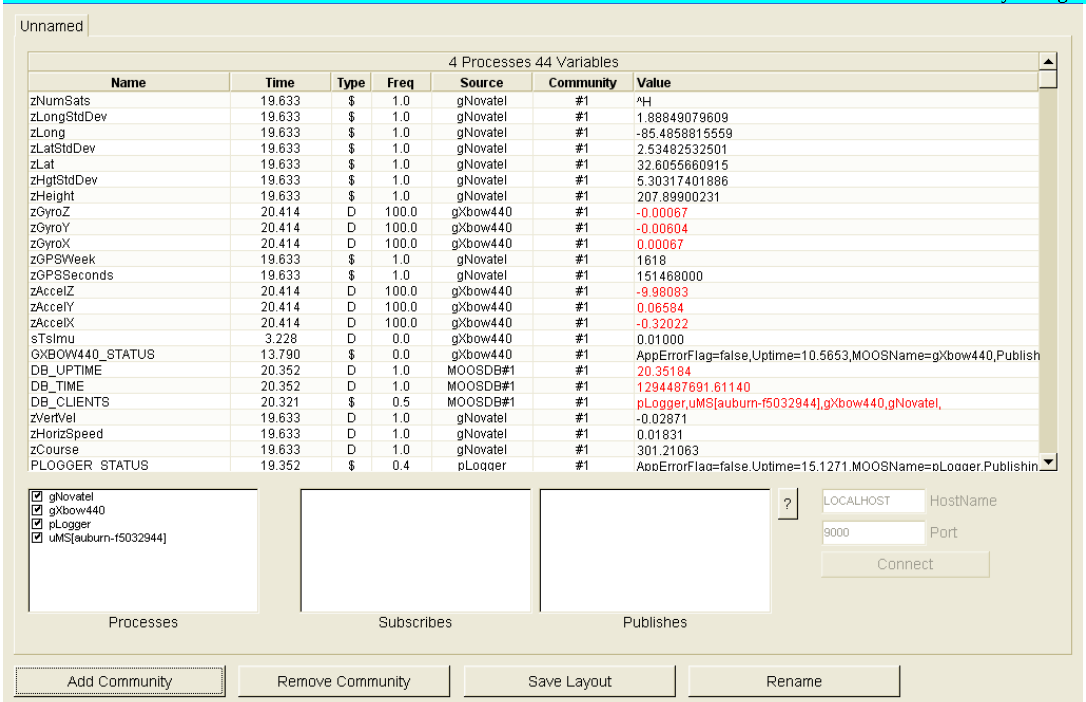

Figure 11: MOOS Database GUI Visualization – Novatel and XBOW

The so-called mission files enable the user to choose which sensors to run, how the sensors are to be configured, and data to record in the database with only the modification of a text file. This allows for quick inclusion or exclusion of experimental testing out on the track without the need for significant software changes. With a single command line, the multiple sensor systems can be launched for recording data or just a single system depending on the needs of testing while at the track.

Auburn University has implemented the majority of their sensors into the MOOS framework. All sensors (Novatel, Septentrio, XBOW) as well as the sensors from the previous FHWA project (LiDAR and camera lane positioning) have been thoroughly tested using the MOOS system. In addition, pose estimates and covariances from SRI's (formally Sarnoff) Visodo system has been saved in the MOOS database. Data from Kapsch and Penn State's systems will be interfaced into the MOOS framework as well.

2.4.2 Integrated Positioning System

The Integrated Positioning System (IPS) will incorporate each system's output into a final positioning solution using an Extended Kalman Filter (EKF).

Time Update

The time update for the IPS system follows the same structure as the well known GPS/INS system time update and will not be explained in detail here. The time update uses the Inertial Measurement Unit (IMU) to propagate the state vector and state covariance matrix forward in time. Inputs from the IMU are used in the standard kinematic equations with integration and determining pose. For more information see [9].

EKF Measurement Update

An Extended Kalman filter is used to blend the range measurement(s) with other available measurements into one solution that has the same update rate as the onboard IMU. The state vector of the Kalman filter (X) is given below:

$$X = [\vec{r}^{e}_{eb} \quad \vec{v}^{e} \quad \vec{\psi}^{e} \quad \vec{b}^{b}_{a} \quad \vec{b}^{b}_{g} \quad \overrightarrow{dt}_{gps}]$$

The state vector contains estimates of the position, velocity, and attitude of the vehicle along with the IMU bias and GPS receiver clock bias/drift. $\vec{r}^{e}_{eb}$ is a three state vector containing the estimated three-dimensional position of the vehicle in the ECEF coordinate frame. $\vec{v}^{e}$ is a three state vector containing the estimated three-dimensional velocity of the vehicle in the ECEF coordinate frame. $\vec{\psi}^{e}$ is a three state vector containing the estimates for the three Euler angles that describe the attitude of the vehicle. The attitude is expressed in terms of the three necessary rotations to rotate the ECEF coordinate frame to align with the body coordinate frame. The values of $\vec{\psi}^{e}$ does not provide an intuitive view of the attitude of the vehicle. The conventional roll, pitch, and yaw angles can be calculated using the $\vec{\psi}^{e}$ vector when the location of the vehicle is also known ($\vec{r}^{e}_{eb}$). $\vec{b}^{b}_{a}$ is a three state vector containing the estimated IMU accelerometer biases given in the IMU or body coordinate frame. $\vec{b}^{b}_{g}$ is a state vector containing the estimated IMU gyro biases also given in the body coordinate frame. $\overrightarrow{dt}_{gps}$ is a two state vector containing clock values necessary to use GPS pseudorange and Doppler frequencies measurements. The $\overrightarrow{dt}_{gps}$ is only necessary if these measurements are used; therefore, the state vector can consist of 15-17 states depending on the type of GPS measurements currently being used.

Ranging Measurement Update

Typically, it takes four observations from four different GPS satellites to maintain observability of a traditional navigation filter. Previous work has shown when using vision and a lane map, a traditional navigation filter will still remain operation with only two GPS observations. For this project, we have set out to test the effects of using ranges provided by Kapsch from DSRC radios to supplement GPS during times of limited satellite visibility. DSRC ranges can be used to update a navigation filter the same way GPS observations are used to update the current filter. The only difference is when dealing with DSRC ranging, there is no need to solve for a receiver clock bias. Assuming vision measurements and a map are available, it is expected that only one DSRC range is needed to maintain an operational navigation filter under a complete GPS block out. This is due to the fact that there is no receiver clock bias that needs to be estimated.

The figure below shows a bird's eye view of the NCAT test track. Red lines are drawn on the map that represent the lines of sight to a typical GPS satellite constellation. A blue line is drawn to represent a range provide by DSRC.

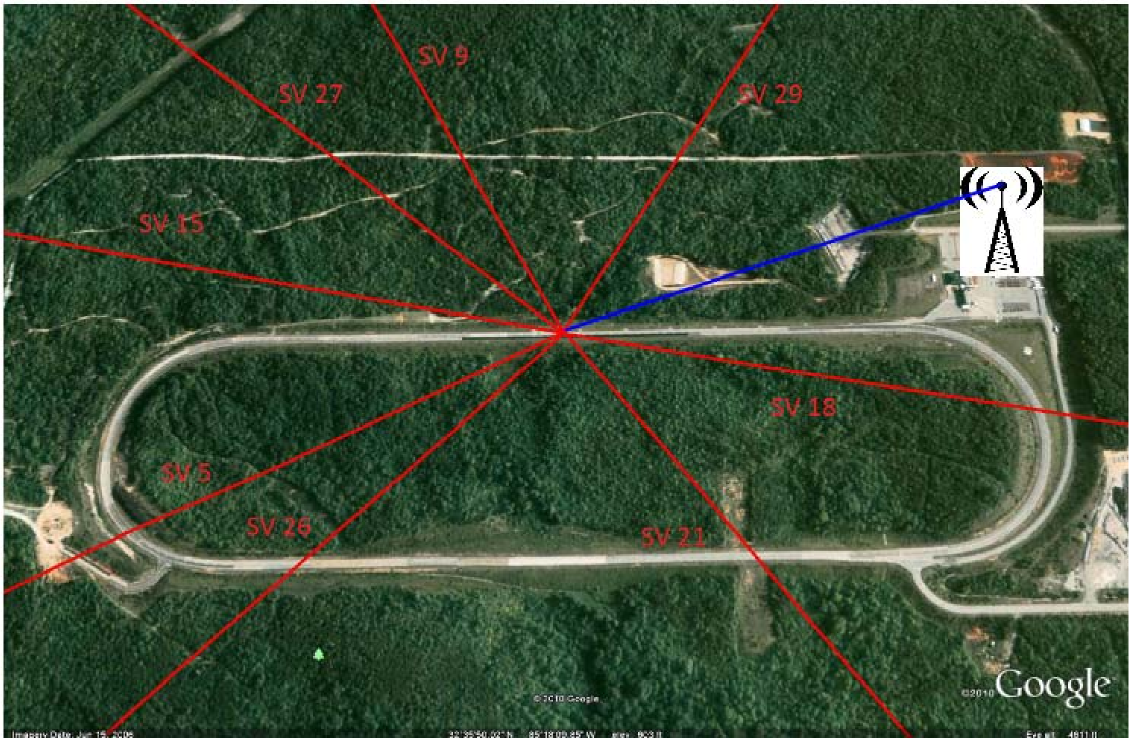

Figure 12: Typical GPS Satellite Configuration

Figure 12 shows a top down view of the track courteous of Google Earth. Drawn on the map are line of sight vectors to GPS satellites for a typical GPS constellation. The blue line is drawn to represent a DSRC range. In a situation where no GPS observations are available, the navigation filter lacks observability in the axis parallel with the road. Ideally, the line of sight vector from the vehicle to the DSRC base station will lie in the axis parallel with the road. This would allow for best observability during a satellite failure. In the figure above, the location of the DSRC base station would provide good observability of the axis parallel with the road on the north straightaway.

In order to use the DSRC ranges as measurement updates for the Kalman filter, an equation that estimates the range is needed. The distance formula can be used estimate the range between the vehicle and the DSRC base station and is given below:

$$\hat{\rho} = \hat{\rho} = \sqrt{(x_b - X_1)^2 + (y_b - X_2)^2 + (z_b - X_3)^2}$$

This equation is the measurement function and is a function of the first three states of the navigation filter ($\hat{r}^{e}_{eb}$=[X_1 X_2 X_3]) and the position of the base station ([x_b y_b z_b]) in the ECEF coordinate frame. Subtracting the base station position vector from the estimated vehicle position and dividing each element by the estimated range will result in a estimated unit vector that points from the base station to the vehicle ($\vec{z}$). The elevation and azimuth angle between the vehicle and the base station can be computed using the unit vector $\vec{z}$.

$$\vec{z} = \left[\frac{X_1 - x_b}{\hat{\rho}} \quad \frac{X_2 - y_b}{\hat{\rho}} \quad \frac{X_3 - z_b}{\hat{\rho}}\right]$$

The measurement model matrix (H) is a Jacobian matrix that is the result of taking the partial derivative of the measurement equation with respect to each state. It turns out that the three values of the unit vector given above are equal to the first 3 values in the H matrix. The rest of the values are zero as there are no other states in the measurement equation.

$$H = \frac{\partial \hat{\rho}}{\partial X} = [\vec{z} \quad \cdots \quad 0]$$

The H matrix is an m x n matrix where m is the number of measurements, and n is the number of states. If more than one DSRC range is available, then the unit vector for each range can be stacked in the H matrix as follows:

$$H = \begin{bmatrix} \vec{z}_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ \vec{z}_m & \cdots & 0 \end{bmatrix}$$

Road Fingerprinting Measurement Update

Penn State's road fingerprinting provides a global solution. When road fingerprinting is available, the H matrix is as follows:

$$H = \left[I_{3x3} \quad 0_{3x3} \quad 0_{3x3} \quad 0_{3x3} \quad 0_{3x3} \quad 0_{3x2}\right]$$

where

$$I = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Visual Odometry Measurement Update

SRI's Visual Odometry (Visodo) provides a global solution with one caveat – the solution will drift overtime without GPS corrections. Visodo gets GPS positions from the receiver and automatically updates the global position to correct for drift. However, if GPS cannot update Visodo, the solution will drift. A drifting measurement in the EKF will result in a drifting position estimates. To prevent this from occurring, Auburn will determine the maximum time that Visodo can provide reasonable position estimates. when Visodo global position estimates are available, the H matrix is as follows:

$$H = \begin{bmatrix} I_{3x3} & 0_{3x3} & 0_{3x3} & 0_{3x3} & 0_{3x3} & 0_{3x2} \end{bmatrix}$$

where I_{3x3} is an identity matrix. Additional information given by SRI's Visodo system will be incorporated into the filter depending on the amount of drift in the Visodo system.

Measurement Update Gain Calculation

After setting up the measurement models from each sensor (which may occur at separate times), the EKF must update the state vector *X* and the state covariance matrix *P*. The R matrix is the measurement covariance matrix. It is m x m diagonal matrix. The diagonal elements of the matrix are set to the expected variance of the error in each measurement.

$$R = \begin{bmatrix} \sigma_1^2 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & \sigma_m^2 \end{bmatrix}$$

The Kalman gain can be calculated using the H and R matrices along with the P matrix. The P matrix is the filter's state covariance matrix. The equation for the Kalman gain is given below:

$$K = PH(HPH + R)^{-1}$$

The measurement residual vector (Γ) is needed to update the state matrix. This vector computed by subtracting a (mx1) vector containing the estimated measurement values from a (mx1) vector containing the actual recorded measurement. The estimated measurement values are computed using the equation for $\hat{y}$ given above.

$$\Gamma = \begin{bmatrix} (y_1 - \hat{y}_1) \\ \vdots \\ (y_m - \hat{y}_m) \end{bmatrix}$$

The state vector is updated using the equation below:

$$X = X + K\Gamma$$

The state covariance matrix must also be updated using the equation below:

$$P = (I - KH)P$$

3. Future Work

3.1 SRI Future Work

3.1.1 Continued data analysis

Data analysis of recorded data includes comparing visual positioning with and without IMU, in different weather conditions, and with different simulated GPS outages and degradation.

3.1.2 Return of sensor package and laptop to Auburn for data collection and integration

Expected time is 2/4/2011.

3.1.3 Software development

Development includes:
- output pose in NED instead of UTM coordinate frame
- improvement of GPS alignment algorithms.

3.2 Penn State Future Work

3.2.1 Field testing of real-time implementation

Additional field tests of the real-time algorithm will be conducted in the present quarter. The Simulink model will shortly be made available to our colleagues at Auburn University to interface and include into the Integrated Positioning System (IPS).

3.2.2 Road Network Implementation

A road network implementation for vehicle will require creating multiple estimators to maintain tracking. For instance, when a vehicle crosses an intersection, it can move along any one of the various available roads. An estimator would thus be required for each of the possible paths taken. Work is currently underway to modify the real-time implementation so that the algorithm can work in a road network with multiple estimators running simultaneously. Currently, the algorithm is being configured to calculate and accept multiple initial conditions to be fed into the multiple estimators.

3.2.3 Future Plans

Penn State's plans for the near future involve rigorous testing of the SPKF algorithm and Simulink model in a real-life environment. Additionally, as mentioned earlier, work is already underway to incorporate the possibility of road intersections and road networks into the algorithm's functionality. By the next quarterly report, it is expected that the algorithm will be tested for a simulated intersection and work would be underway for integration of the road network and real-time functionalities of the algorithm.

3.3 Kapsch Future Work

Kapsch will continue to explore strategies for more accurately determining DSRC ranging. In addition, Kapsch is looking for strategies for measuring angle of arrival at DSRC base antenna.

3.4 Auburn University Future Work

Auburn will continue to work with partners to interface and mount the sensors on the test vehicle.

3.4.1 MOOS

Auburn University will interface the data being sent from Penn State and Kapsch's system with the MOOS framework. With each sensor available for recording, system testing should be significantly easier when the full system is finally tested.

Time synchronization is a difficult problem for any data collection system. Currently, time synchronization has proven to not be a significant problem while using the MOOS system. Auburn University will continue to monitor the time synchronization to ensure that faulty timestamps are not a problem in the data collection.

3.4.2 Integrated Positioning System

Since each system has not yet been implemented on the test vehicle, Auburn University will simulate the performance of the IPS using simulated data of each of the sensors. Initial work will use MATLAB for simulation. When the vehicle is fully implemented, the IPS will be written in C++ for cohesion with MOOS.

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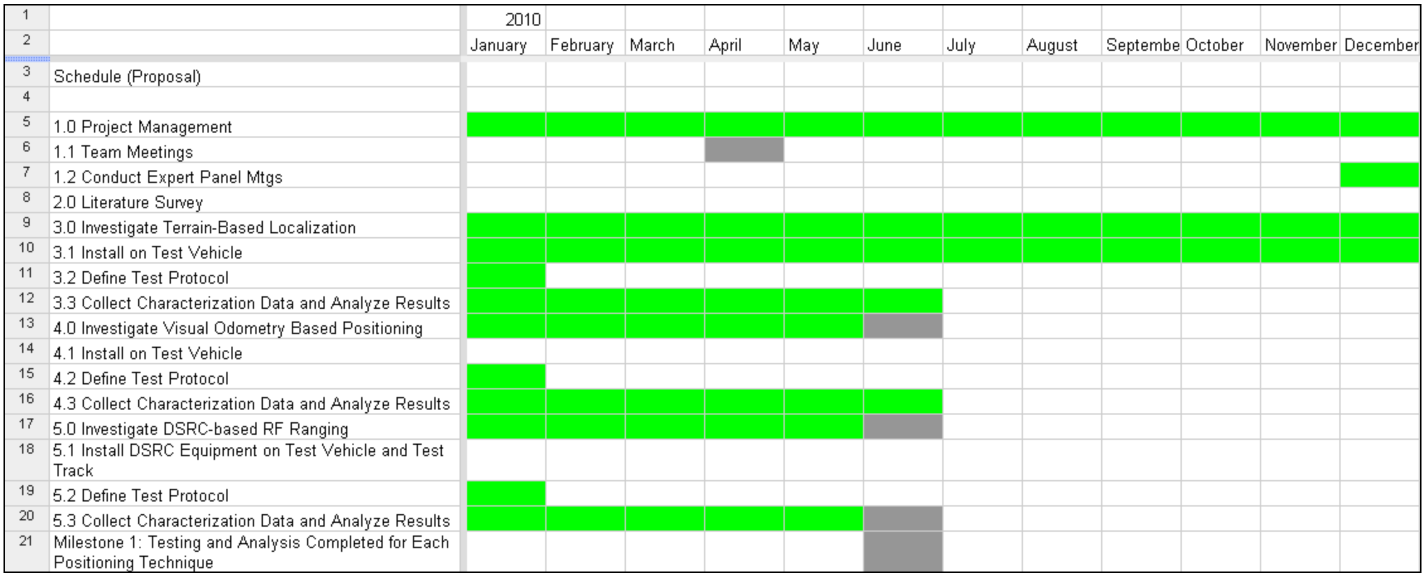
Gantt Chart


2010
January
February
March
April
May
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July
August
Septembe
October
November
December
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