

# WPI Precision Personnel Locator System: Inertial Navigation Supplementation

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## BIOGRAPHY

Mr. Vincent Amendolare is a Ph.D. candidate in Electrical and Computer Engineering at WPI. Since completing his BS and MS degrees at WPI in 2006 and 2007, he has served as a research assistant in the WPI Convergent Technology Center sponsored by the NIJ/DOJ on the topic of precision personnel location. His MS thesis determined techniques to attain synchronization necessary for the WPI precision personnel location system, and his Ph.D. research concerns improving the performance of this system with inertial navigation supplementation.

Dr. David Cyganski is professor of Electrical and Computer Engineering at WPI where he performs research and teaches in the areas of linear and non-linear multidimensional signal processing, communications and computer networks, and supervises the WPI Convergent Technology Center. He is an active researcher in the areas of radar imaging, automatic target recognition, machine vision and protocols for computer networks. He is coauthor of the book *Information Technology: Inside and Outside*. Prior to joining the faculty at WPI he was an MTS at Bell Laboratories and has since held the administrative positions of Vice President of Information Systems and Vice Provost at WPI.

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## ABSTRACT

This paper describes the latest developments in the Worcester Polytechnic Institute (WPI) Precision Personnel Location (PPL) system. An RF-based system with inertial sensor supplementation is being developed for tracking of first responders and other personnel in indoor environments. The system assumes no existing infrastructure, no pre-characterization of the area of operation and is designed for spectral compliance and rapid deployment. The RF 3D location system has previously demonstrated sub-meter positioning accuracy of a transmitter even in difficult indoor environments with high multi-path with all receivers outside the building. However, accuracy can be severely degraded at particular locations within a building such as when a large and nearby metal panel blocks the direct path from the mobile transmitter to several receiving antennas. This paper describes the performance of our existing RF location system's raw position estimate performance and how these raw position estimates may be filtered with motion constraints via the Kalman filter for improved accuracy. The paper goes on to investigate the use of inertial sensors to supplement the information from our RF position estimates, and how this information is fused together to provide improved overall system performance.

## I. INTRODUCTION

Previous papers by the authors [1-6] have described the general system architecture, precision location approach, hardware design challenges, signal structure, and experimental results paralleling the development and refinement of the system's hardware realization. Fig. 1 is an artist's rendition of the PPL concept. The goal of the system is to provide a robust real-time tracking solution that requires no pre-installed infrastructure. To be tracked, firefighters and other emergency personnel each carry a transmitter emitting a multi-carrier wide-band (MC-WB) signal [4], which is sensed at receiving

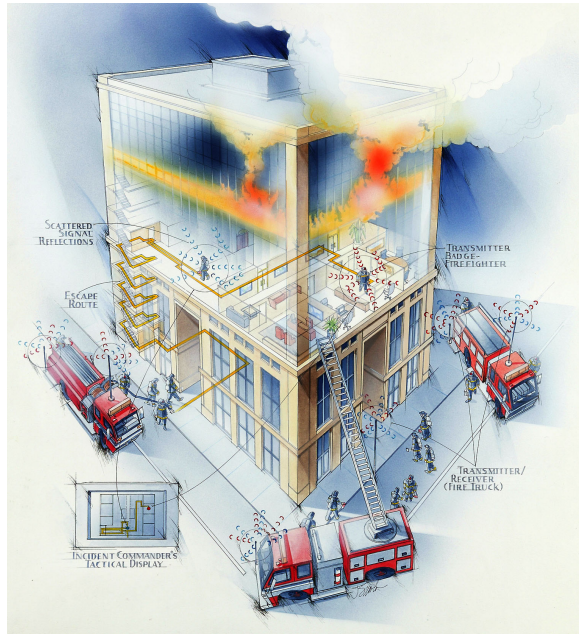


Fig. 1. PPL concept illustration

TABLE I  
LOCATION TESTING MEAN ABSOLUTE ERRORS

Test Location	Error	Bandwidth
Kaven Hall	0.37 m	60 MHz
Atwater Kent	1.08 m	60 MHz
Campus Ministry 1st fl.	0.59 m	60 MHz
Campus Ministry 2nd fl.	0.72 m	60 MHz
Campus Ministry 1st fl.	0.49 m	150 MHz
Campus Ministry 2nd fl.	0.46 m	150 MHz

stations fixed upon emergency response vehicles. Upon arrival, the receiving stations form an ad-hoc network and establish a local coordinate system.

Given the receiving stations' positions within the local coordinate system, the signals collected at each station are transferred to a central location where the relative positions of the transmitters within the coordinate system are estimated. These estimates are then conveyed to command-and-control software in the hands of the incident commander. Accumulation of track information for many transmitters has the effect of providing the incident commander with valuable information on building layout to assist with exit guidance or search and rescue operations. Efforts are also underway to integrate additional information into the incident commander's display to enable monitoring of personnel physiological status and ambient environmental conditions.

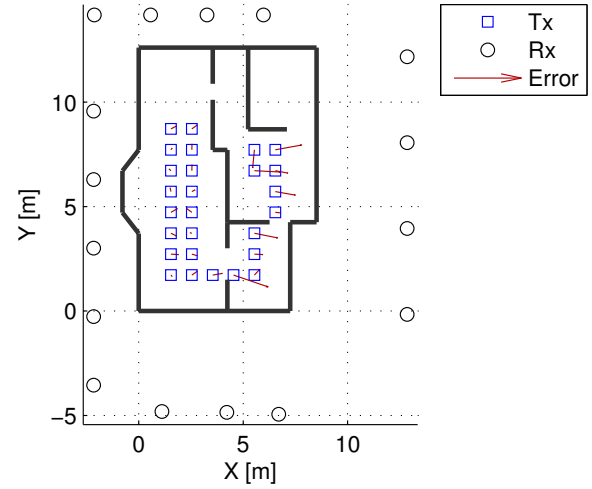


Fig. 2. Campus Ministry: Mean Absolute Error - 0.49m

## II. EXPERIMENTAL LOCATION TESTS

Publications [2] by the authors have presented location testing results from a 60 MHz RF system and from a new 150 MHz wideband system [1]. The results of these tests are summarized here in Table I; all results involve 2D location of a transmitter inside the building by antennas placed outside of it. The Kaven Hall test location comprises brick and steel-beam construction and houses a geotechnical lab on the WPI campus; the Atwater Kent location was a larger scale test centered around the wing of a large brick building, passing through steel-studded walls and under metal-corrugated ceilings; and the Campus Ministry location is a typical wood-construction three-story residential structure complete with furniture and metal appliances in the kitchen. The errors in Table I provide a reference for the general accuracy of our system.

Fig. 2 displays a result from the Campus Ministry test on the first floor with 150 MHz of bandwidth. The circles represent our receive antenna (Rx) locations outside the house, while the squares represent several transmitter (Tx) locations at which the transmitter was truly positioned. At each location the transmitter was stationary and its position was estimated using the received RF signals at the receive antennas. The plot shows error vectors which point from the true location of the transmitter to the estimated position. We see that in many cases the error is quite small, however some locations are more challenged due to direct path blockage and reflections.

The positioning algorithm used in our system is computationally intensive and takes approximately 0.3

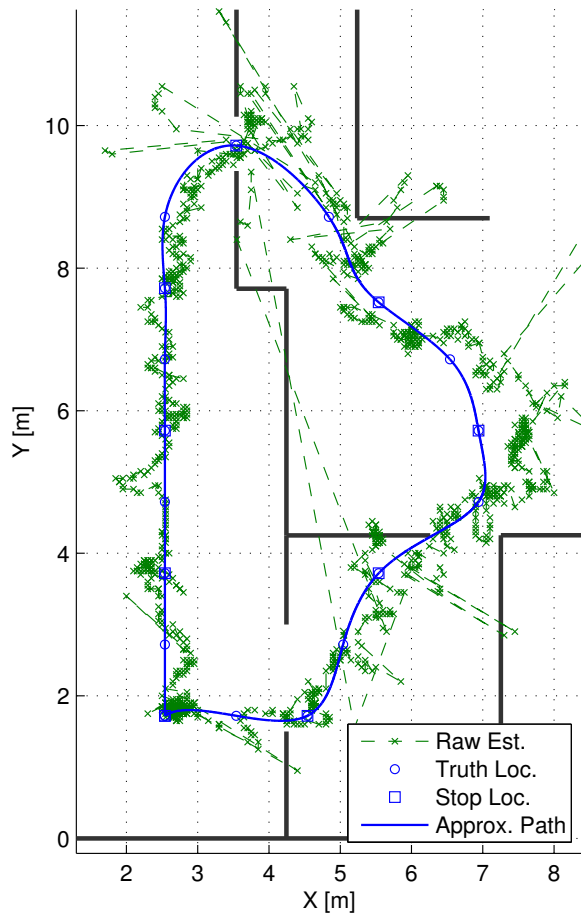


Fig. 3. Campus Ministry - Continuous Capture

seconds to compute a position estimate with our current microprocessor based hardware. It is possible however for us to capture signal data at a faster rate continuously and post-process it. During a recent test at the Campus Ministry we performed a continuous data collection at a rate of approximately 30 captures per second while the transmitter was moved around the first floor of the house. The result of this data set is shown in Fig. 3. The transmitter was moved through several surveyed truth locations depicted by blue circles. The blue line is a spline curve passing through the truth locations that approximately describes the true path of the transmitter. Note that the transmitter was brought to a complete stop at the stop locations (depicted by blue squares). This result provides great insight into how our position estimates change as the transmitter is moved. We see that generally it follows the true path. There are apparently two types of errors. There are highly localized large deviations from the truth path; fortunately these are often only present for isolated samples so they can be more easily rejected in a tracking implementation. There are

also consistent deviations from the true path that last for several samples. Fortunately these are relatively small (less than 1 meter) and return shortly to the truth path. This same data set will be used throughout this paper for comparison of different tracking approaches.

Based upon motion constraints of the person we wish to track, these raw solutions can be filtered to obtain a more precise tracking estimate.

### III. TRACKING WITH KALMAN FILTER

Our system can be modeled as a discrete time linear system with state variables in a vector  $\mathbf{x}_k$ , where  $k$  is a discrete time index. The states in our system are the position, velocity and acceleration column vectors of the tracked personnel denoted  $\mathbf{p}$ ,  $\mathbf{v}$ ,  $\mathbf{a}$  respectively.

$$\mathbf{x} = \begin{bmatrix} \mathbf{p} \\ \mathbf{v} \\ \mathbf{a} \end{bmatrix} \quad (1)$$

The value of  $\mathbf{x}_{k+1}$ , the next state is a function of the current states and a process noise term  $\mathbf{w}_k$ . This process noise term is a random vector, which models the changes in states of the tracked personnel as a random process.

$$\mathbf{x}_{k+1} = \mathbf{A}\mathbf{x}_k + \mathbf{w}_k, \quad (2)$$

where the  $\mathbf{A}$  is the state transition matrix that describes the dynamics of the state variables. For our case

$$\mathbf{A} = \begin{bmatrix} \mathbf{I}_3 & \tau\mathbf{I}_3 & \mathbf{0}_3 \\ \mathbf{0}_3 & \mathbf{I}_3 & \tau\mathbf{I}_3 \\ \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{I}_3 \end{bmatrix}, \quad (3)$$

where  $\tau$  is the elapsed time between  $k$  and  $k + 1$ . This state transition matrix derived from the fact that velocity is the derivative of position, and acceleration is the derivative of velocity.

Our system provides raw position estimates which can be represented as

$$\mathbf{y}_k = \mathbf{C}\mathbf{x}_k + \mathbf{v}_k \quad (4)$$

where  $\mathbf{C}$  is called the observation matrix and  $\mathbf{v}$  is the measurement noise. For our case since our system measures position  $\mathbf{C}$  simply masks out the velocity and acceleration

$$\mathbf{C} = \begin{bmatrix} \mathbf{I}_3 & \mathbf{0}_3 & \mathbf{0}_3 \end{bmatrix}. \quad (5)$$

The errors in our raw position measurements are modeled by  $\mathbf{v}$ .

This system model we have developed is the system model for a discrete time Kalman filter [7]. This filtering technique is a common solution to the problem

of tracking with noisy estimates. The Kalman filter is optimal for estimating the parameters of linear systems with Gaussian noise. The noise in our system may not be truly Gaussian, but it may be approximated as such. For our system we assume that the process and measurement noise both have zero mean. The covariance of each of these noise sources must be known.

The Kalman filter algorithm has two phases, prediction and update [8]. The prediction phase makes a prediction of the state variables from the state estimate  $\hat{\mathbf{x}}_{k-1}$  of the previous time step.

$$\mathbf{x}_k^- = \mathbf{A}\hat{\mathbf{x}}_{k-1} \quad (6)$$

The Kalman filter not only estimates the state variables, but it also keeps track of the covariance of the state variables. The Kalman filter treats the state variables as a multivariate Gaussian with a covariance matrix  $\mathbf{P}_k$ . The prediction phase also involves the prediction of the covariance matrix based upon the estimate from the previous time step  $\hat{\mathbf{P}}_{k-1}$ .

$$\mathbf{P}_k^- = \mathbf{A}\hat{\mathbf{P}}_{k-1}\mathbf{A}^T + \mathbf{Q} \quad (7)$$

where  $\mathbf{Q}$  is the covariance matrix of the process noise.

The second phase of the Kalman filter algorithm is the update phase [8]. First the Kalman gain  $\mathbf{K}_k$  is computed.

$$\mathbf{K}_k = \mathbf{P}_k^- \mathbf{C} (\mathbf{C}\mathbf{P}_k^- \mathbf{C}^T + \mathbf{R})^{-1} \quad (8)$$

where  $\mathbf{R}$  is the covariance matrix of the measurement noise. The Kalman gain takes an important role in the next step, where it acts as a relative weight between the predicted state  $\mathbf{x}_k^-$  and the actual measurement  $\mathbf{z}_k$  to produce the filtered measurement  $\hat{\mathbf{x}}_k$ .

$$\hat{\mathbf{x}}_k = \mathbf{x}_k^- + \mathbf{K}_k (\mathbf{z}_k - \mathbf{C}\mathbf{x}_k^-) \quad (9)$$

Similarly the covariance matrix  $\mathbf{P}_k$  is estimated.

$$\hat{\mathbf{P}}_k = (\mathbf{I} - \mathbf{K}_k \mathbf{C}) \mathbf{P}_k^- \quad (10)$$

This process is repeated for each new measurement.

In our system we use the discrete time Kalman filter to improve our tracking performance based on estimates of our position estimate noise variance and personnel motion process variance. This method of tracking based on position estimates will be denoted as the “position only” Kalman filter algorithm. The primary difference between our implementation and the classic Kalman filter described above is outlier rejection logic intended to ignore large, isolated errors. Fig. 4 shows a set of raw position estimates from our RF system as well as the filtered version of this data. The sample rate for this

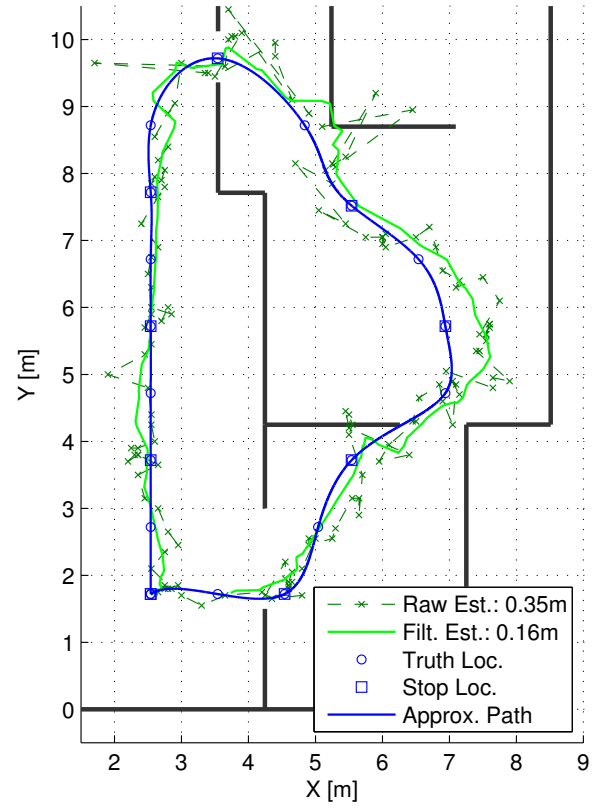


Fig. 4. Raw estimates and filtered estimates

data was reduced to approximately 3 updates per second to replicate realistic timing for our real-time positioning hardware.

The error relative to the approximate truth path was calculated before filtering to be 0.35 meters and after filtering to be 0.16 meters. This is a significant improvement and yields our desired accuracy of better than one foot. We are still interested in techniques for further improvement because we expect our raw position estimates to be worse in more challenging multipath environments, hence the next pursuit of inertial supplementation to be discussed below.

#### IV. INERTIAL SUPPLEMENTATION

This paper investigates the potential benefit of supplementing our existing RF based positioning system with inertial sensors to improve overall performance. Recent work has been aimed towards proof of this concept.

We have been working with the nIMU (nano Inertial Measurement Unit) created by Memsense. This unit contains a three axis accelerometer, three axis gyroscope and three axis magnetometer with measurements at a rate of 150Hz in a small form factor [9]. For our testing this unit was boxed and attached to a cart along with our RF



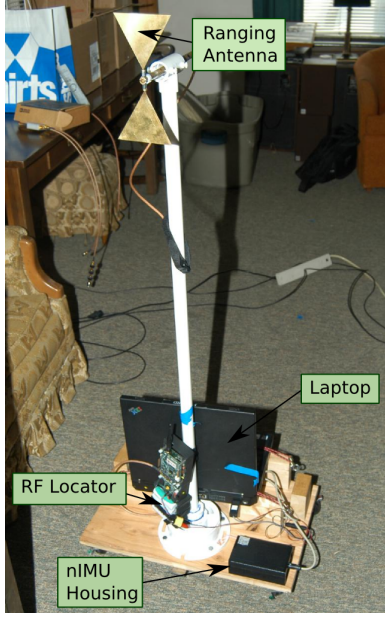


Fig. 5. Locator Cart

locator and a laptop for nIMU data logging, as shown in Fig. 5.

One significant issue with inertial measurement units is calibration. While inertial measurements are generally considered to have Gaussian noise, they also may have deterministic errors. The most prominent of these are biases and incorrect scale factors. Our device was characterized by the manufacturer to determine these values in order to calibrate the device. Temperature can affect these values as well, and although the nIMU features internal temperature compensation [9], its biases and scaling values can still change considerably. Ideally the device would be fully calibrated immediately before tracking, however an elaborate calibration procedure is not practical for our system in the field. We employ a simple calibration procedure, holding the device stationary for a few seconds, before tracking begins. This allows us to determine any gyroscope bias and also estimate the initial pitch and roll of the device from the accelerometer measurements.

Before an attempt was made to integrate inertial and RF position estimates we observed how well we could track the unit with inertial data alone. The algorithm used to do this is based upon the Kalman filter implementation described previously.

First the orientation of the cart (which we will call the cart frame) relative to our system's local coordinate system must be tracked. This relative orientation is a rotation in three dimensions, which can be described

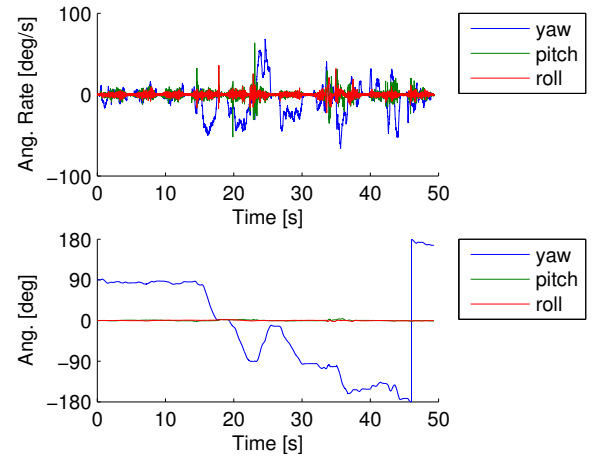


Fig. 6. Orientation Tracking

by an orthogonal rotation matrix  $\mathbf{R}_c^l$ . This matrix will map any vector  $\mathbf{a}_c$  in the cart coordinate system to its equivalent vector in the local coordinate system  $\mathbf{a}_l$ .

$$\mathbf{a}_l = \mathbf{R}_c^l \mathbf{a}_c \quad (11)$$

This rotation matrix can be parameterized by three Euler angles. For our implementation we use the aeronautics convention of yaw, pitch and roll. Which refer to positive rotations about the z, y and x axis sequentially [10].

As the orientation of the cart changes over time, this rotation matrix changes. The derivative of this matrix can be expressed as

$$\dot{\mathbf{R}}_c^l(t) = \mathbf{R}_c^l(t) \boldsymbol{\Omega}_c^l \quad (12)$$

where  $\boldsymbol{\Omega}_c^l$  is the skew symmetric representation of the three angular rates  $(\omega_{c_x}^l, \omega_{c_y}^l, \omega_{c_z}^l)$ , the angular rates about the three axes of the cart measured by the gyroscopes [12].

$$\boldsymbol{\Omega}_c^l = \begin{bmatrix} 0 & -\omega_{c_z}^l & \omega_{c_y}^l \\ \omega_{c_z}^l & 0 & -\omega_{c_x}^l \\ -\omega_{c_y}^l & \omega_{c_x}^l & 0 \end{bmatrix} \quad (13)$$

In discrete time, the orientation  $\mathbf{R}_{c,k}^l$  can be estimated from the previous estimate and the current gyroscope measurement.

$$\mathbf{R}_{c,k}^l = \mathbf{R}_{c,k-1}^l \left( 2\mathbf{I}_3 + \boldsymbol{\Omega}_{c,k}^l \tau \right) \left( 2\mathbf{I}_3 - \boldsymbol{\Omega}_{c,k}^l \tau \right)^{-1} [12] \quad (14)$$

This is currently being done with our three axis gyroscope measurements. This is certainly not a valid long term solution as it is tracking based on angular rate, open loop; however for the short data captures we have been working with thus far (1-2 minutes) it has proven to be quite accurate. Fig. 6 shows the orientation

tracking for the same data set we have been treating (in Fig. 3 and Fig. 4).

As the cart was wheeled about the floor, it remained flat on the floor for the most part, thus its pitch and roll remained fairly constant. It's yaw however varied considerably as shown in Fig. 6. There was no way for us to measure our true orientation over time for comparison with our estimated orientation. We will soon observe however that using this orientation information for inertial tracking can yield quite accurate results, implying that our orientation is being well tracked.

The accelerometers in the nIMU measure the motion induced acceleration of the device summed with the acceleration of gravity. Our local coordinate system is chosen such that gravity is in the  $-z_l$  direction. The acceleration due to gravity can be represented in the local coordinate system as

$$\mathbf{g}_l = \begin{bmatrix} 0 \\ 0 \\ -g \end{bmatrix} \quad (15)$$

where  $g$  is the magnitude of acceleration due to gravity (approximately  $9.80665 \frac{m}{s^2}$ ). The measurement of the accelerometer in the cart frame  $\mathbf{f}_c$  is

$$\mathbf{f}_c = \mathbf{R}_c^{lT} (\mathbf{a}_l + \mathbf{g}_l) \quad (16)$$

where  $\mathbf{a}_l$  is the acceleration of the object in the local coordinate system. Thus  $\mathbf{a}_l$  can be estimated at discrete time index  $k$

$$\hat{\mathbf{a}}_{l,k} = \mathbf{R}_{c,k}^l \mathbf{f}_{c,k} - \mathbf{g}_l \quad (17)$$

These local frame acceleration estimates can be processed by our Kalman filter if we change our observation matrix to

$$\mathbf{C} = \begin{bmatrix} \mathbf{I}_3 & \mathbf{0}_3 & \mathbf{I}_3 \end{bmatrix}. \quad (18)$$

Or if we have acceleration measurements and no position measurements

$$\mathbf{C} = \begin{bmatrix} \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{I}_3 \end{bmatrix}. \quad (19)$$

For our implementation we have inertial measurements at 150Hz and position estimates at approximately 2-3Hz, so our observation matrix changes depending on which measurements are present.

Fig. 7 shows the outcome of tracking our data set with inertial information alone. We see that our estimated path quickly diverges from the true path. A small bias in our angular rate measurements causes our estimated orientation to deviate from our true orientation. Thus when we attempt to subtract the effect of gravity it will

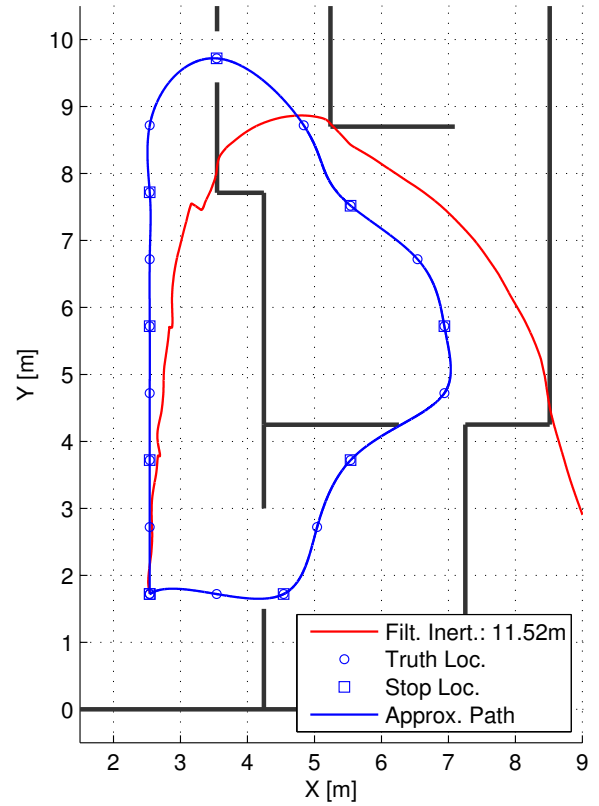


Fig. 7. Inertial Tracking

not be canceled perfectly and leave some residue. This residue acts as a bias on our acceleration measurements (in the local coordinate frame), which quickly yields a large position error.

One common and powerful technique to curb the error growth in inertial navigation systems is to use zero velocity updates (ZUPTs).[11] If the unit is known to have zero velocity at some moment in time this information can be used to reset some of the growing errors in the Kalman filter. First, the velocity state in the Kalman filter may be set to zero. Second, between two zero velocity update times the average acceleration in the local frame must be zero. To take full advantage of this fact, one must wait for a ZUPT to repair the inertial data from before that ZUPT and use it for tracking. This is acceptable if the time between ZUPTs is short and some lag in the tracking solution is acceptable. For the analysis in this paper it has been assumed that this lag is acceptable. As our system is intended to track personnel it is possible for us to obtain these ZUPTs if our unit is placed on a part of the body that stops frequently such as the foot.

Recall for our data set the cart was brought to a complete stop at the locations depicted on the truth path.

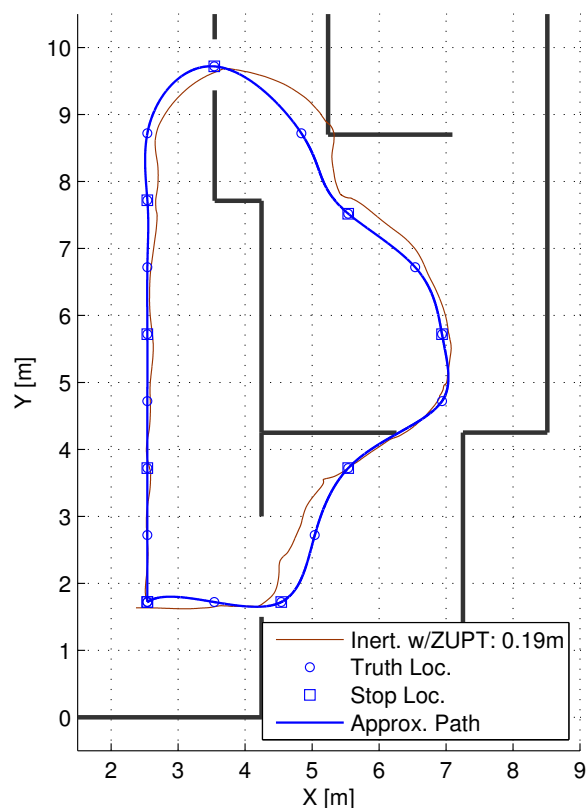


Fig. 8. Inertial Tracking with ZUPTs

We can take advantage of these with ZUPTs to improve our tracking performance dramatically. Fig. 8 shows the tracking performance with inertial information and ZUPTs. We see that the error is now 0.19m, comparable to our position only tracking result. The data set was taken over a short enough period of time that this technique resulted in estimates which did not deviate significantly from the true path. This is certainly not a viable long term solution however as it is an open loop inertial tracker and the path estimate will thus ultimately diverge due to sensor bias.

The goal of these investigations is to use both the position estimates from our RF system as well as inertial information to create an accurate long term stable tracking system. Since the inertial tracker is quite accurate in the short term we can apply a small weight on information from our RF position estimates in our Kalman filter. Our RF position estimates may have large errors, but as long as they don't tend towards a certain direction (that is, as long as they have zero mean) they will keep the inertial tracker from slowly drifting away from the proper path. Using this fusion of data in our Kalman filter we achieve the result shown in Fig. 9. We obtain the smallest error seen thus far for this data set at

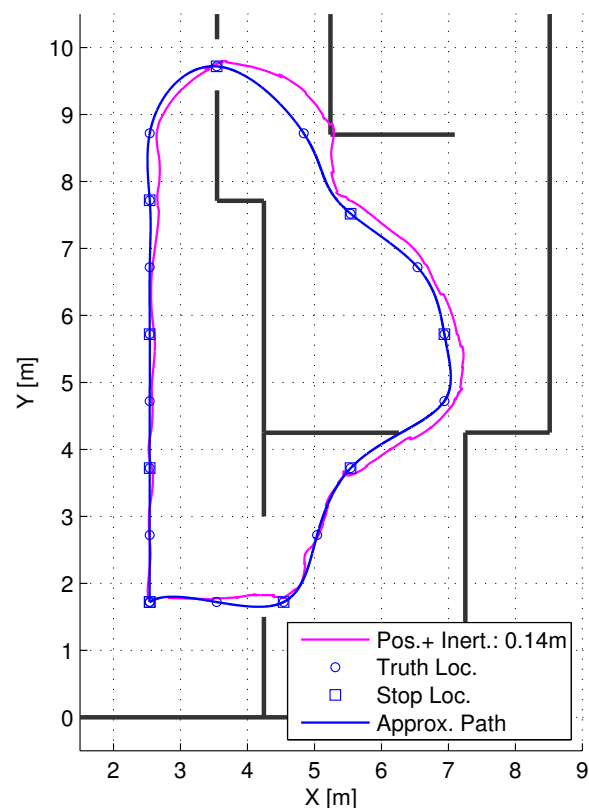


Fig. 9. Tracking with Inertial and RF Position Estimates

0.14m. While this is not dramatically smaller than our position only tracker, it does show inertial information can be used to improve the RF tracking while providing RF based amelioration of inertial drift that would eventually accumulate and then rapidly degrade position information. In more challenging environments such as larger buildings we expect our RF position estimates to present larger errors if employed alone, while the inertially supplemented solutions will be substantially unaffected.

## V. FUTURE WORK

The idea of an inertial supplementation to our RF system seems promising at this time but more work is required to bring it to full fruition. Future research will focus on the several areas of effort described below.

We still need to close the loop on our orientation tracking, as currently we are only using gyroscope measurements. The most common solution to this problem is to use the direction of measured gravity as a pitch and roll reference and magnetometer measurements as a yaw reference. We are investigating means to use our RF information to provide more reliable information for this purpose. This will likely involve a solution with coupling

between orientation tracking and position tracking such as an extended Kalman filter. [12]

We wish to evaluate our tracking performance in more difficult RF environments, as well as with tracking over a longer period of time.

Results in this paper were obtained by post-processing. Ultimately the inertial supplementation will need to be integrated into our real-time tracking system. As the inertial unit must be worn by the personnel to be tracked, the recorded data must be sent wirelessly to our signal processing station.

## VI. CONCLUSIONS

This paper has explored the proposed idea of improving WPI's existing RF-based Precision Personnel Location system by adding information from an inertial measurement unit. We have shown that indeed such information can improve the tracking performance of our system compared to tracking with RF position estimates alone.

## ACKNOWLEDGMENT

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