WPI Precision Personnel Locator: Inverse Synthetic Array Reconciliation Tomography

A. Cavanaugh, M. Lowe, D. Cyganski, R. J. Duckworth

BIOGRAPHY

Mr. Andrew Cavanaugh is a PhD. candidate in Electrical and Computer Engineering at WPI. Since completing his B.S. EE degree at The University of Rhode Island in 2008, he has served as a research assistant in the WPI Precision Personnel Location Laboratory, where he earned his M.S. degree in 2010. His research is focused on improving the accuracy of the WPI Precision Personnel Location system, using Bayesian methods to fuse diverse sources of information, and designing environmental monitoring devices for firefighters. He is a member of ION, and the IEEE.

Mr. Matthew Lowe has been attending WPI since 2005, and is working towards his PhD. degree in Electrical and Computer Engineering in the Precision Personnel Location Laboratory. Mr. Lowe has done funded research in the areas of applied mathematics, signal processing, Kalman filtering, and inertial navigation. Currently he is working on implementing a flexible framework to effectively incorporate inertial information into VSLAM applications. He is a member of ION, and the IEEE.

Dr. David Cyganski is a Professor in the Electrical and Computer Engineering department at WPI where he performs research and teaches in the areas of linear and non-linear multi-dimensional signal processing, communications and computer networks. While an active researcher in the areas of radar imaging, automatic target recognition and machine vision, he has devoted much of the past decade to developing technology for precision location, safety and situational awareness for firefighters within WPIs Center for First Responder Technologies. Prior to joining the faculty at WPI he was an MTS at Bell Laboratories and has held the administrative positions of Vice President of Information Systems and Vice Provost at WPI. He is a member of ION and the IEEE.

Dr. R. James Duckworth is an Associate Professor in the Electrical and Computer Engineering department at WPI. He obtained his Ph.D. in parallel processing from the University of Nottingham in England. He joined WPI in 1987. Duckworth teaches undergraduate and graduate courses in computer engineering focusing on microprocessor and digital system design, including using VHDL and Verilog for synthesis and modeling. His main research area is embedded system design. He is a fellow of the BCS, a senior member of the IEEE, and a member of ION and the IEE.

ABSTRACT

This paper describes the latest algorithm being developed by the Worcester Polytechnic Institute (WPI) Precision Personnel Location (PPL) project. Our goal is to produce a rapidly deployable, ad-hoc system that can achieve sub meter positioning accuracy in any type of emergency response scenario using available spectrum; specifically we wish to locate first responders in and around buildings. Previous work [1] has led to separate or loosely coupled approaches for fusing RF and inertial positioning data, as well as data from other sensors.

The Inverse Synthetic Array Reconciliation Tomography (ISART) algorithm is a fusion of RF and inertial measurements that is fundamentally different from previous systems. Instead of fusing positioning results, we use the inertial displacements to coherently fuse successive RF captures. The benefits of this approach are twofold. First, the fusion depends only on relationships between inertial values spanning small time intervals, so that we do not accumulate large inertial drift errors. Second, the RF conditions at each point are expected to be very different because high multi-path environments are very sensitive to spatial perturbations. Since the multi-path signal components are changing rapidly with position we expect that only the direct path signals will be correlated between successive RF data captures taken from unique positions. In order for the direct path signals from different locations to be correlated these captures must be aligned for fusion with the inertial displacement data. The ISART algorithm performs this signal alignment and computes a metric based on this direct path correlation using the sample processing employed by the Singular Value Array Reconciliation Tomography (σART) algorithm [2]; the ISART solution is the point where the metric is maximal.

I. INTRODUCTION

The goal of this research is to produce a system for precision indoor location that is more accurate than the RF [3], [4], [5] and inertial [6] components of the PPL system alone, by fusing RF positioning solutions with inertial tracking data in a tightly coupled manner. Specifically, we are interested in extending the range of operations from small residential structures to large scale commercial and industrial facilities where RF coverage will be compromised, and pure inertial tracking would be difficult. Inertial position estimates are the outcome of a double time integral, which causes their error to grow with time \( t^2 \), as mentioned in [5]. RF systems, on the other hand, do not suffer from any accumulation of error over time, but the errors vary with position in an unpredictable and erratic manner. The main source of error in RF position estimates is multi-path, which (given sufficient SNR) is a
and the function $R$ is a slowly changing unknown yaw angle offset, $C_{RF}(x)$ is the covariance of the RF position estimates at position $x$, $C_{INS}(i)$ is the covariance of the accelerometer noise at the $j$th time-step, and $t$ is time. Once the observation model is defined we can easily construct a Kalman Filter to track the state based on multiple independent observations of the state.

In this implementation, for experimental convenience, the inertial data is processed off-line, and the filtered positions are fed into the ISART algorithm. An extension of this implementation would be to use a single filter which treats simultaneously the raw RF and inertial samples. Here we will treat the inertial filter as a black box that gives us samples in real time. When considering a practical system we will see that this is indeed a reasonable assumption. It is also possible to make RF captures coincide with zero-velocity updates (zupts) so that we can feed high quality position and velocity information to the INS filter simultaneously for further enhancement.

A block diagram of the system architecture for the ISART algorithm is shown in Fig. 1. The RF and inertial hardware capture data simultaneously, and this data is processed off-line. In this configuration the inertial system only feeds data to the ISART algorithm, but the inertial Kalman Filter can easily be adapted to accept position updates from the ISART algorithm [6]. We can adjust the amount of confidence placed in the INS or RF system by varying the length of the time window (number of RF captures) over which we fuse RF data. If the inertial data is very accurate then we can fuse many more RF samples by increasing this window length, reflecting our confidence in the inertial solution for the relative relationships between the locations at which the RF captures were made.

III. SIMULATIONS

In this section we present the results of simulations conducted to test the efficacy of the ISART algorithm for indoor location. The simulations use code adapted from the simulations conducted for [3], [4], [5]; this simulation works at the signal level and is considered a fair representation of the performance of an algorithm in free space with the ability to simulate perfect reflectors to introduce multi-path into the RF data. The results of the simulations are plotted in Figs. 2-4 with the locations of reference antennas (white circles), the target being tracked (white square), ideal reflectors (green triangles), and the ISART solution (black X) overlaid on the graphical representation of the metric function. The metric function is evaluated at every point in a scan grid as in the graphical representation of the metric function. The metric function is evaluated at every point in a scan grid as in the metric function of an algorithm in free space with the ability to simulate perfect reflectors to introduce multi-path into the RF data. The results of the simulations are plotted in Figs. 2-4 with the locations of reference antennas (white circles), the target being tracked (white square), ideal reflectors (green triangles), and the ISART solution (black X) overlaid on the graphical representation of the metric function. The metric function is evaluated at every point in a scan grid as in the metric function of the ISART algorithm [2]. The metric values are color coded in these images with blues representing low values and reds representing high values.

Since the ISART algorithm is fusing data from multiple RF captures, we executed a simulation in which the locator remains stationary, but still performs the ISART processing as a control case. The control case effectively averages successive
RF captures, which is expected to mitigate errors caused by channel noise, but should have little to no effect on the multi-path errors. Fig. 2 shows the outcomes of the control case simulation. As can be seen, the solution is markedly wrong as a sub-optimal peak in the $\sigma$ART metric was chosen owing to the large multi-path conditions resulting from the signal reflectors (triangles) that were introduced in this simulation.

In Figs. 3 and 4 the reference antennas are placed in the same locations as in Fig. 2, and the additional white circles represent the virtual (the fusion process synthesizes additional antenna locations to compensate for the motion of the target) locations of these antennas in the fused ISART data matrix. Figs. 3 and 4 show ISART results based on the same path being taken by the target being tracked. To investigate the performance of ISART with more realistic inertial information we simulated the effects of noisy accelerometer measurements. This noisy inertial case is shown in Fig. 4 where the effects of the noise can be seen when comparing the locations of the virtual antennas with those of 3.

Fig. 3 shows a simulated case for ISART with a window length of ten samples, and simulated perfect inertial knowledge. This simulation shows that if we know our inertial displacements absolutely, we can indeed mitigate the effects of multi-path in the RF channel; the correct peak is now selected and the location error is only 0.22 m. This confirms our assumptions that multi-path effects are extremely sensitive to spatial perturbations, and with ISART processing, the direct path signals will be fused constructively.

Finally, Fig. 4 shows the result of the third simulation case, in which the inertial displacement estimates were corrupted.
by the noise added to the underlying accelerometer data. Here we found that the ISART algorithm is robust enough to work with realistic inertial data sources. We had expected that the ISART processing would produce errors that were smaller than those seen in the control case, but larger than the errors in the results produced by the perfect inertial case. In fact, the error in the noisy inertial case was nearly identical to that seen in the perfect inertial case.

There is clearly a significant improvement in the results with motion captures vs. the result of the control case. At the level of noise shown in Fig. 4 the error in the ISART solution was not affected.

**IV. EXPERIMENTAL RESULTS**

This section details the results of two field tests that were used to verify the functionality of the ISART algorithm using actual hardware and experimental conditions. The results of these field tests are presented as error vector plots (see Figs. 5-7). These plots show truth locations as gray squares, which are at the tails of the error vectors. The color of each error vector corresponds to the algorithm that produced the error, and the head is the location that the algorithm yielded as a solution. Thus the magnitude of each position error is the length of the corresponding error vector. The RMS errors for all of the methods are summarized in the plot title.

**A. WPI Campus Religious Center**

The first test that we conducted, in the WPI Campus Religious Center, was a post-processed result in which survey data was used as a surrogate for inertial data. This house is quite typical for a city dwelling in New England, and the first floor is furnished no differently than any other residential dwelling (kitchen, living room, dining room). Using data from a past field test we were able to simulate the ISART algorithm on real RF data, but with simulated perfect inertial knowledge (based on our known truth data). The comparison of error vectors is shown in Fig. 5. We can also apply our noise model from the simulations to the truth points to mimic a more realistic inertial track, as in Fig. 6.

In a practical situation, it would obviously make more sense to just trust the inertial system in both of these cases (this is trivially true in the “perfect inertial” case). It should be noted that the inertial data to which we are comparing the ISART results has been initialized manually, while the ISART algorithm works with non-initialized inertial data. In other words, the inertial navigation solution and the ISART algorithm both use the same raw inertial data, but the inertial navigation solution needs to be provided with an initial location and heading in order to produce meaningful results. In our experiments we surveyed the initial point and provided a marked path for the initial heading, but in a more realistic scenario, the initial point and heading would need to be estimated. Regardless of these initialization considerations, the ISART algorithm was able to improve the σART solution with only knowledge of the inertial displacements between points.

![Fig. 5. Comparison of the ISART algorithm with σART on real RF data (post-processed) and perfect inertial data](image1)

![Fig. 6. Comparison of the ISART algorithm with σART on real RF data (post-processed) and noisy simulated inertial data](image2)
In order to get a better idea for the real world performance of the ISART algorithm we conducted a real time field test in Alden Hall.

B. Alden Hall

A real time test was conducted in Alden Hall, a large, open, auditorium and involved a person walking along a path with points surveyed at each foot fall. The inertial zupts were synchronized with RF data captures so that we could easily synchronize the two data sources for ISART processing. Since the RF conditions in Alden Hall have line of sight between all nodes, we only used three reference antennas, which is the minimum number needed to perform TDOA-like localization in two dimensions. This environment provided a relatively clean channel with some geometric dilution of precision, and a relatively mild multi-path channel.

The Alden Hall test confirmed that the ISART algorithm is capable of producing a solution that is more accurate than both the RF and INS solutions individually. Fig. 7 shows the RF-only (σART) , inertial only, and ISART error vectors. Note that the path both starts and ends at the upper right hand corner, and moves counter clockwise around the triangle. Since the loop is closed, we have a double set of error vectors at the first point. The initial inertial error is shown here as zero, which represents perfect knowledge of the initial point. Note that ISART does not need to know this initial information. In this test the ISART error was much better than the σART error, as expected, and the performance was also better than the inertial-only system, which suggests that the ISART algorithm can be of practical use in a real world situation.

V. CONCLUSIONS AND FUTURE WORK

We have shown that ISART can significantly improve positioning accuracy even with relatively noisy inertial information. Both simulated results, and actual field tests support this conclusion. A limitation of the current ISART implementation is that there is no automatic rule for determining the number of the RF captures to fuse for a single ISART computation. In all of the results presented in this paper, the window length was unconstrained, but on longer walks with more RF samples this would create problems stemming from both the growth of the received data, and from the known drifting of the inertial solution with time. In a sense, the window length is the weighting parameter between the amount of confidence in the inertial data source and the amount of confidence in the RF data source. A logical next step would be to close the feedback loop between the inertial and RF systems by giving the inertial Kalman Filter positioning information from the outcomes of ISART processing (see Fig. 8). It is worth noting here that the ISART algorithm is a general approach for fusing any σART -like data source with any additional data source such as inertial navigation or machine vision.

REFERENCES