A Bayesian Fusion Algorithm for Precision Personnel Location in Indoor Environments

A. Cavanaugh, M. Lowe, D. Cyganski, R. J. Duckworth
Worcester Polytechnic Institute, Worcester, Mass.

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. His research is focused on improving the accuracy of the WPI Precision Personnel Location system, using Bayesian methods to fuse diverse sources of information. He is a member of ION, and the IEEE.

Mr. Matthew Lowe has been attending WPI since 2005, and is currently 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, and is currently focused on developing the tools necessary to efficiently fuse information from pressure, inertial, magnetic, and other sensors for use in location solutions.

Dr. David Cyganski is Professor of Electrical and Computer Engineering at WPI where he performs research and teaches linear and non-linear multidimensional signal processing, communications and computer networks. 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. He is a member of IEEE and a member of ION.

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, a member of ION and the IEE.

ABSTRACT

An RF-based system is being developed at WPI 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. A 3D location system, based on a multicarrier signal using a novel signal fusion algorithm has been previously described [1] and has demonstrated sub-meter positioning accuracy of a transmitter, even in difficult indoor environments with high multi-path, with all receivers placed outside the building. The development of new hardware supporting two-way transactions has driven development of new signal fusion algorithms, as well as allowing tight integration with information from an on-board high-quality MEMs IMU system. This paper reports on the development of new processing and filtering techniques that were designed to exploit the new hardware capabilities and that yield performance improvements in comparison with our previously demonstrated systems.

INTRODUCTION: WPI PRECISION PERSONNEL LOCATOR SYSTEM

The goal of the WPI precision personnel location project is to develop a system appropriate for use by first responders incorporating no pre-installed infrastructure, rapid deployability, flexible and spectrally compliant signals, and low cost personnel tags. Previous papers have described: development and performance of novel signal processing and location techniques for the amelioration of the extreme multi-path conditions such as found in typical commercial and industrial structures, which usually frustrate all attempts to achieve precision location [2][3]; incorporation of physiological monitoring sensors and real time display; automated solution of outdoor sensor positions for rapid deployment [4][5]; synchronization technologies for wirelessly connected transceiver nodes [6], and accuracy enhancement through sensor fusion [1]. This paper describes the newest signal processing algorithms being developed for the PPL system. Our new information fusion algorithm is tested in indoor location contexts matching those of previous work so as to establish the performance gains obtained.

This paper presents a new Bayesian Fusion Algorithm that can fuse data from our existing algorithms [2] [3]. Our TDOA-like Singular Value Array Reconciliation Tomography (σART) and our TOA-like Transactional Array Reconciliation Tomography (TART) algorithms are also described in this paper. The Bayesian Fusion Algorithm is based on the type of sensor fusion that was described in [1]. The σART and TART algorithms are shown in this paper to be probabilistic measures, and their independence is verified in [7]. The results of a field test are also presented to compare the performance of the Bayesian Fusion Algorithm with the σART and TART algorithms.

Bayesian Fusion Algorithm

In [1] the authors presented a Bayesian approach to fusing information data from several sensors. The Bayesian Fusion algorithm uses this result, as well as incorporating information from different processing techniques and algorithms applied to the same data. This allows us to make use of the new TART algorithm, while retaining key advantages that were present in the classical σART system. Barometric data to augment height estimation is also included in the fusion.

In order to build an estimator for the position of our locator, it is first necessary to construct probability density functions (PDF), or likelihood functions, that correspond to the received data, as well as the prior information. In our case we will start by assuming a uniform prior, for our estimated position, which is uniform on the area contained in our search space[1]. This relatively simple assumption can be enhanced if any other information about the structure is known, for example the inter-floor spacing, or the location of stairs/elevators. Once all of the prior information is taken into account, we then incorporate our data into the solution via the Bayesian estimation process detailed in [7].

We will assume in this paper, that we are given the PDFs generated from the barometric, σART , and TART data. To estimate the parameters, x, y, z, which are the X, Y, and Z coordinates of our locator, we discretize the posterior distribution into a number of points, which lie on planes that are stacked along the Z-axis. For every point in the discrete scan grid, we evaluate:

$$P(D_\sigma, D_T, D_b|\mathbf{x}, I) \times P(\mathbf{X}|I) \tag{1}$$

for

$$\mathbf{x} = x, y, z$$

The point, x, y, z, where this metric is maximized corresponds to the point in space where the locator is estimated to be, based on the available data.

Singular Value Array Reconciliation Tomography (σART)

Currently, the PPL system utilizes the σART algorithm, a unique algorithm that was developed at WPI [2]. This algorithm is a TDOA-like RF based approach, which considers data from all of the reference antennas as one set, rather than performing individual ranging estimates. The σART algorithm is performed on the received signal sample vector, from a set of p receiving antennas. The received signal, is the multicarrier wide band (MCWB) signal, transmitted by the locator, X, convolved with the channel response between the locator, and a receiving antenna, p. σART is performed on a matrix, $R \in \mathbb{C}_{N\times p}$, whose columns are the N-point FFT of the received signals from the p receive antennas. Each column of $\mathbf{R}$ is, therefore, equal to $\mathbf{R}_p(\omega) = X(\omega)H_p(\omega)$.

The MCWB signal structure is a sum of unmodulated sinusoids [3], evenly spaced in frequency, as shown in Equation (2). Here, we are ignoring initial phase, as well as any time offsets introduced by the hardware.

$$X(\omega) = \sum_{n=0}^{m-1} \delta(\omega - (\omega_0 + n\Delta\omega)) \tag{2}$$

If we consider phase offset in our mixers, $\tilde{\theta}(t)$, and sample clock drift, $\tilde{\tau}(t)$, we obtain a more accurate expression for our transmitted signal in (3). Here, we are assuming that the time-dependency of these offsets is slow enough to represent them as constants for short windows of time.

$$X(\omega)' = \sum_{n=0}^{m-1} \delta(\omega - (\omega_0 + n\Delta\omega))e^{-j\omega\tilde{\tau}-\tilde{\theta}} \tag{3}$$

The received signal is therefore:

$$R_p(\omega) = X(\omega)H_p(\omega)e^{-j\omega\tilde{\tau}_p-\tilde{\theta}_p} \tag{4}$$

The search space is discretized into a "scan grid", and the received data matrix is used to calculate the value of a metric at each point in the scan grid.

σART Metric

In order to estimate a transmitter location from the received signal matrix, a metric is evaluated at every point in the scan grid, a discrete set of points in the solution space. The point where the metric is maximized is the σART algorithm's estimate of the locator's position. To evaluate the σART metric at a given point, the first step is to 're-phase' the received signal matrix:

$$\mathbf{R}' = \left[\mathbf{r}_1 \circ e^{j\omega \overset{\#}{t}_{0,1}} \ldots \mathbf{r}_p \circ e^{j\omega \overset{\#}{t}_{0,p}} \ldots \mathbf{r}_P \circ e^{j\omega \overset{\#}{t}_{0,P}}\right] \tag{5}$$

Where $\overset{\#}{t}_{0,p}$ is the ideal time offset between the scan grid location and the receiving antenna, p. This process is described in detail in [8], [3], [4]. The channel's impulse response will take the form of a set of delayed and scaled impulse functions. The transfer function, $H(\omega)$, is shown in (6), for the case of N_p paths.

$$H_p(\omega) = \sum_{n=1}^{N_p} \gamma_{n,p} e^{jwt_{n,p}} = \gamma_{1,p} e^{jwt_{1,p}} + \sum_{n=2}^{N_p} \gamma_{n,p} e^{jwt_{n,p}} \tag{6}$$

In general, the multipath components are weakly correlated, allowing the σART algorithm to largely ignore their contribution. At the correct scan location, the re-phased direct path components will be highly correlated, and the matrix, $\mathbf{R}'$ will become singular. It is shown in [3] that the energy of the received data matrix is not altered by re-phasing. The non-ideal phase offsets from (4) are also shown to be ignored by the σART algorithm. Since energy of the $\mathbf{R}$ matrix is conserved at every point in the scangrid, we can use the first singular value of the re-phased matrix as the σART metric.

[1]Although we are doing 3D location, the word 'area' is used here because we are scanning 2D slices of a 3D space

σART Metric as a Probabilistic Measure

Since the Bayesian Fusion Algorithm works with probability distributions, we must be able to interpret the information provided by σART in a probabilistic manner. Simulations and perturbation analysis have shown a direct correlation between the relative values of the σART metric, and relative frequency distribution of the location solution with noisy data [3].

The top of Figure 1 is a histogram of the position estimates produced by σART in a Monte Carlo simulation (1,000 trials) with a -6dB SNR [3]. The bottom of Figure 1 is a σART metric function from this same simulation. Both the histogram and the metric function have a peak at the same point. The peaks are also elongated in the same direction. The colored area of the relative frequency histogram is smaller because the solutions from 1,000 trials did not produce solutions in the areas corresponding to very low likelihoods.

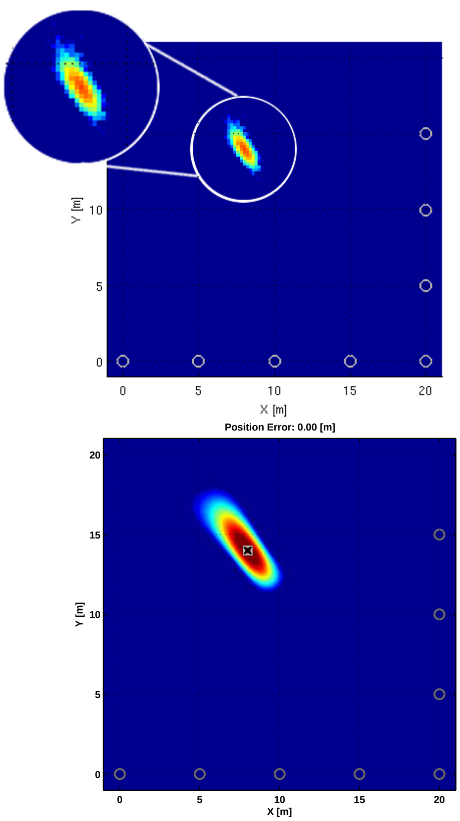

Fig. 1. σART simulation with -6dB SNR: Error histogram 1000 trial Monte Carlo simulation (top), σART metric image from one trial (bottom)

In order to condition the metric for application as a probabilistic measure within the context of estimation theory, we normalize the final metric function, such that the metric values $\in [0, 1]$. To achieve this, we subtract the minimum value and then divide by the new maximum value. The metric is now a normalized discrete likelihood function for the position of a locator.

Transactional Array Reconciliation Tomography (TART)

The TART algorithm is the latest addition to our RF-based location and tracking system. This algorithm is similar to σART, but requires an additional synchronization step, which is performed with a bidirectional exchange between pairs of locators. With this new transactional approach, we are able to achieve TOA-like synchronization. This means that there is no unknown constant time offset across the columns of the received data matrix, Eq. (4) now in effect becomes Eq. (7)

$$R_p(\omega) = X(\omega)H_p(\omega)e^{j\tilde{\theta}_p} \tag{7}$$

The means to accomplish this synchronization are described in detail in [3]. New hardware is currently being developed to allow us to use TART in real time [9], but post-processing has enabled us to perform TART location with our current hardware [3], using the transceiver boxes as both the mobile, and the reference radios.

TART Metric

After synchronization, the re-phasing process is carried out as detailed in Eq. (5). At this point, the metric can be evaluated at every point in the scan grid. While σART required calculation of the first singular value of the re-phased matrix, TART only requires summation across the rows of the re-phased matrix. In an ideal case the summation will be maximized at the correct scan location because the direct path components will all have zero time shift at the correct location when the data is re-phased. The computation time required for evaluating the TART metric is more than 10 times faster than that required for σART [3]. This increased computational efficiency makes TART ideal for real time tracking of multiple locators.

TART Metric as a PDF

The TART metric can also be turned into a normalized likelihood function defined on the scan grid. The same analysis from [3] shows that the relative frequency statistics are proportional to the metric magnitudes. We can thus normalize the metric so that the values are $\in [0, 1]$, allowing us to employ the same processing techniques as used with the σART metric. Scaling the metric preserves the proportionality relationship.

Figure 2 shows the error histogram and TART metric function for a similar Monte Carlo analysis to that which was shown in Figure 1. These two images also have peaks at the same point, with spreading in the same direction. This illustrates the proportionality of the metric function to the distribution of errors.

Experimental Results

The Bayesian Fusion algorithm was developed in order to maintain the accuracy of the PPL system in situations where we have poor antenna coverage, or very low SNR. Situations in which only one side of a building is covered by reference antennas are of particular interest because of the orthogonally skewed distributions of the σART and TART

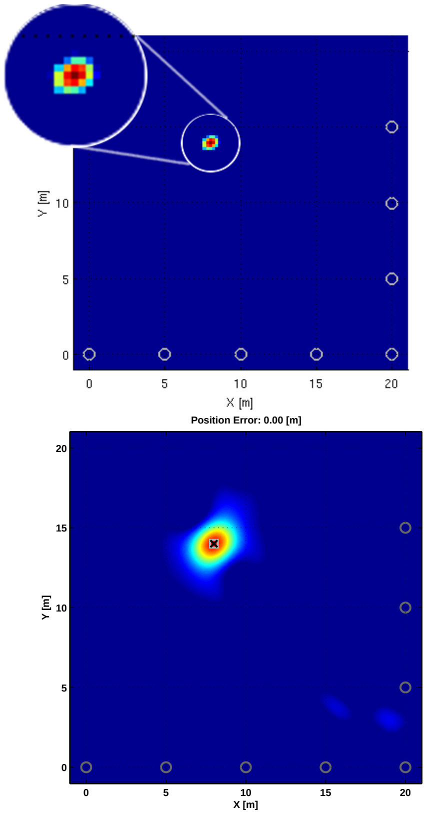

Fig. 2. TART simulation with -6dB SNR: Error histogram 1000 trial Monte Carlo simulation (top), TART metric image from one trial (bottom)

likelihood functions. While all 3 sources of data affect the final 3D solution, it is clear that in the case of a planar array of antennas on the y, z plane (where the z axis corresponds to height), σART provides the best data about the x coordinate (in the direction perpendicular to the plane of antennas), TART is most accurate in the y coordinate, and the barometric information is the best source for z information. While the barometric sensor never gives us data regarding the x, y position of the locator, knowing what 2D plane to scan in can greatly reduce the ambiguity in the σART and TART data sources. Being able to work in less ideal settings is a critical part of having the capability to deploy the system in a realistic setting, where time and space for system deployment are tightly constrained.

On May 27, 2010 a test of the PPL system was conducted in the west wing of the Atwater Kent (AK) building on the WPI campus. This test was the first to simultaneously capture σART, TART, and barometric data in a rapid deployment scenario. Sixteen patch antennas were affixed to four ladders which were leaned against a wall of the west wing of the building as shown in Figure 3. This wing of the building comprises three stories and a basement. The top half of the basement is above-grade on one side of the building. The structure is brick with a modern steel and dry-wall interior. There are also numerous large pieces of machinery, and no windows, on the western-most wall. We collected data on the basement, first, and second floors.

Fig. 3. West wing of Atwater Kent

The basement of Atwater Kent is interesting because the layout is that of a typical office building, but the environment itself is challenging. Challenging RF conditions include being partially below-grade, only having windows on one side of the building, and being surrounded by elevator and HVAC equipment. The layout of the truth points for the basement is shown in Figure 4. The labeled blue squares correspond to truth locations, with blue circles representing the locations of the reference antennas, seen on the ladders in Figure 3. The numbered truth locations are referenced in Table I.

The first floor is the most interesting case, because it is a lecture hall with theater seating, which allowed us to place truth locations at many different heights, rather than having uniform, discrete, floor heights. This test setup truly tests our accuracy in full 3D. The layout of the truth points on the first floor is shown in Figure 5.

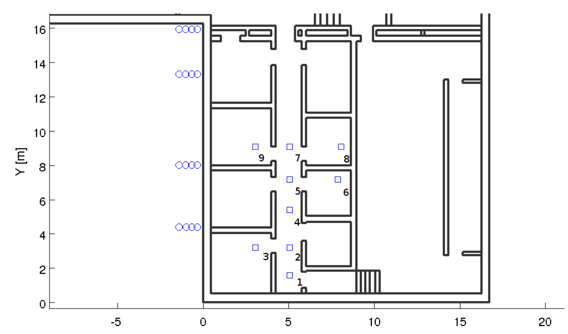

Fig. 4. Atwater Kent Basement Truth Locations from 5/27/2010

Figures 6-9 show the error vectors for the three algorithms at each truth location. The tail of the vector is at the truth location, and the head is located where the corresponding algorithm estimated the position to be. Table I shows the errors from the σART and TART algorithms, as well as the fused

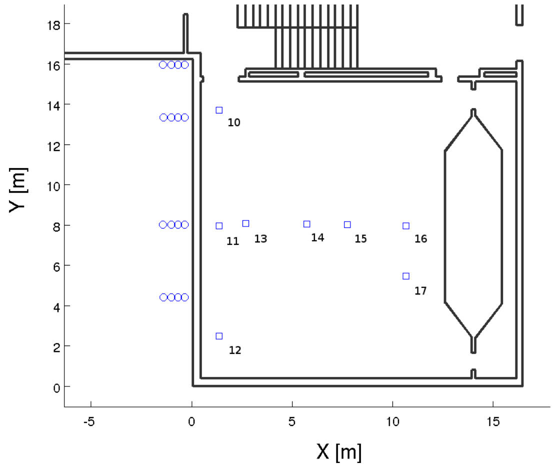

Fig. 5. Atwater Kent First Floor Truth Locations from 5/27/2010

results. The Z error in the Fusion results directly corresponds to the error in barometric height estimates.

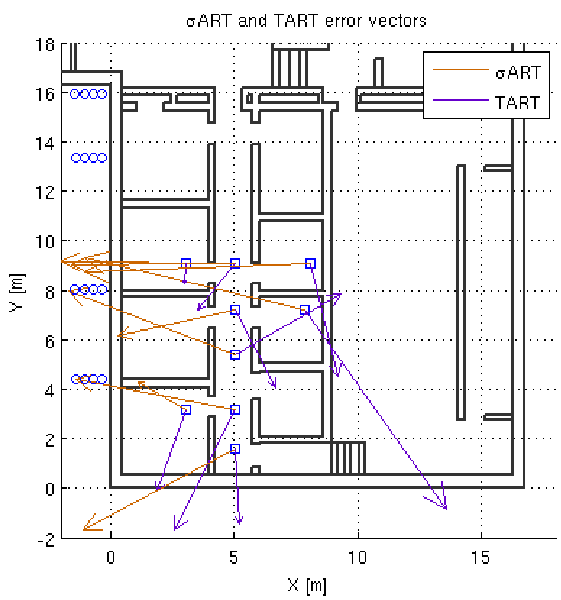

Fig. 6. σART and TART Error Vectors for AK Basement

The large outliers seen in Figure 9 have two likely causes. The first being the proximity of truth points 16 and 17 to the metal backed blackboards that occupy the entire wall of the room where the large hexagon appears. The second factor is the fact that the direct path is likely blocked, since these points are at the lowest point in the auditorium, which only has windows at the higher elevations. The best example of a successful fusion from this test is at truth point #12, on the first floor of Atwater Kent. The σART and TART metric functions are shown in Figure 10, along with the fused result for this particular point; here the XY error was reduced from over 2 meters to just 0.74 meters.

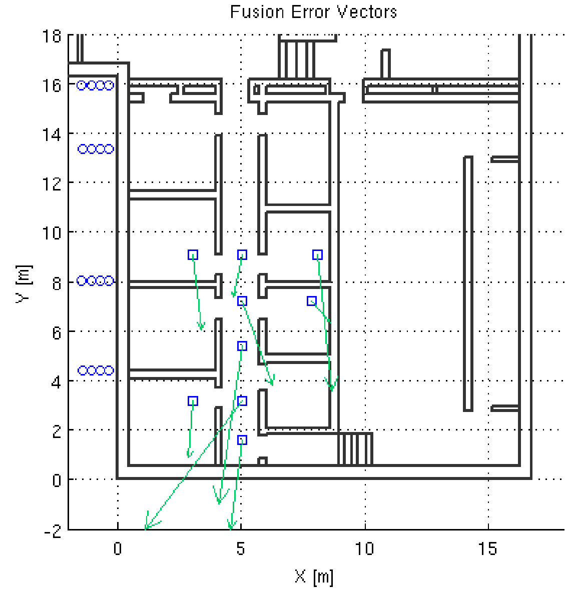

Fig. 7. Fusion Error Vectors for AK Basement

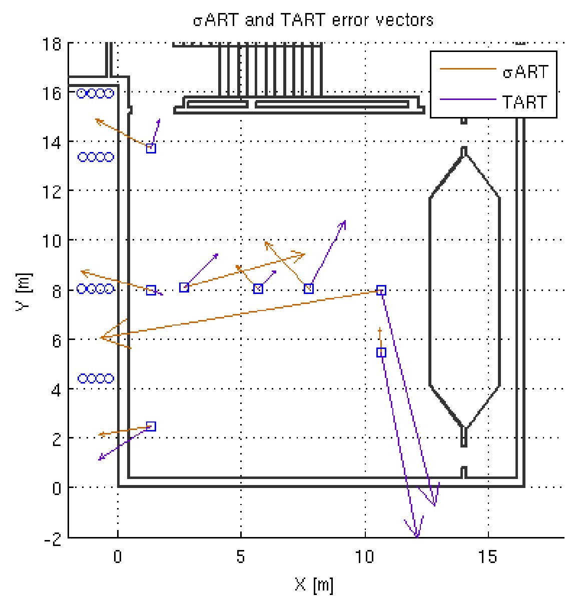

Fig. 8. σART and TART Error Vectors for AK Lecture Hall

Conclusions

To date we have successfully demonstrated the ability to track multiple first responders with sub-meter 1-floor accuracy in residential structures, while relaying position information, as well as physiological and environmental data to a graphical user interface (GUI) that has been developed with extensive guidance from the first responder community. The σART and TART algorithms have allowed us to meet our accuracy goals in small residential structures, even with limited antenna coverage. When we extend our operations to medium scale commercial structures, the Bayesian Fusion Algorithm increases the robustness of solutions, and was shown in

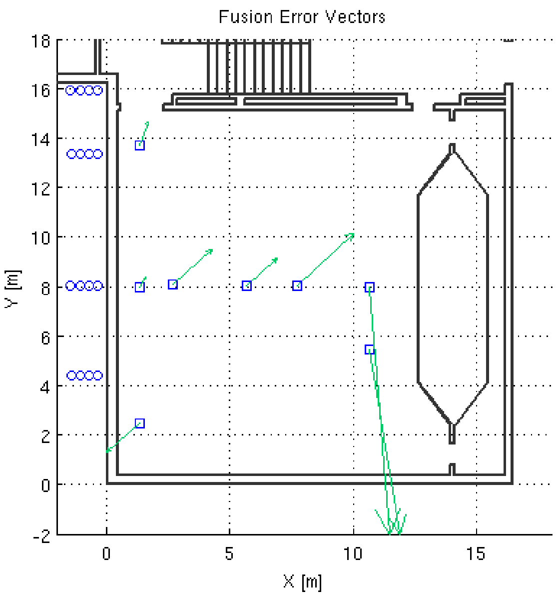

Fig. 9. Fusion Error Vectors for AK Lecture Hall

Method	XY Error [m]			Z Error [m]			XYZ Error [m]		
	σ	T	F	σ	T	F	σ	T	F
1	6.96	3.04	3.62	2.75	0.52	0.00	7.48	3.08	3.62
2	6.58	5.46	6.53	1.36	0.77	0.00	6.72	5.51	6.53
3	2.24	3.51	2.32	0.77	0.00	0.00	2.37	3.51	2.32
4	7.24	4.90	6.42	0.12	0.00	0.00	7.24	4.90	6.42
5	4.87	3.52	3.61	0.52	0.52	0.00	4.90	3.56	3.61
6	9.17	9.87	1.14	2.93	6.18	0.00	9.63	11.65	1.14
7	7.06	2.42	1.73	0.00	5.12	0.00	7.06	5.66	1.73
8	9.11	4.71	5.53	3.02	0.00	0.00	9.60	4.71	5.53
9	4.60	0.81	3.07	0.82	6.95	0.00	4.67	7.00	3.07
10	2.47	1.21	1.67	0.06	0.58	3.49	2.48	1.34	3.87
11	2.93	0.50	0.31	0.81	0.48	2.46	3.03	0.69	2.48
12	2.12	2.52	0.74	0.38	0.20	2.46	2.16	2.53	2.57
13	5.07	1.95	1.57	1.41	0.66	2.78	5.27	2.04	3.20
14	1.26	0.98	1.01	1.42	1.92	1.66	1.90	2.16	1.95
15	2.58	3.12	3.08	1.73	1.88	0.18	3.11	3.65	3.08
16	11.48	8.97	9.87	2.90	4.15	0.75	11.84	9.89	9.90
17	0.97	7.61	7.57	1.77	0.29	0.03	2.02	7.61	7.57

TABLE I
ATWATER KENT ERRORS FOR σART (σ), TART (T), AND FUSION (F) SOLUTIONS

simulation [7], and the case of the first floor of Atwater Kent to improve the overall accuracy of the system. The Atwater Kent basement was very challenging for all of our algorithms, and demonstrates the limitations of the Fusion Algorithm in extremely harsh RF environments. If we look at 2D accuracy (to remove the error introduced by barometric sensors), in Table II we see that the Bayesian Fusion algorithm improved accuracy in both tests.

Location	XY Error [m]		
Test	σ	T	F
Basement	6.42	4.25	3.78
First Floor	3.61	3.36	3.23

TABLE II
SUMMARY OF ATWATER KENT ERRORS IN 2D

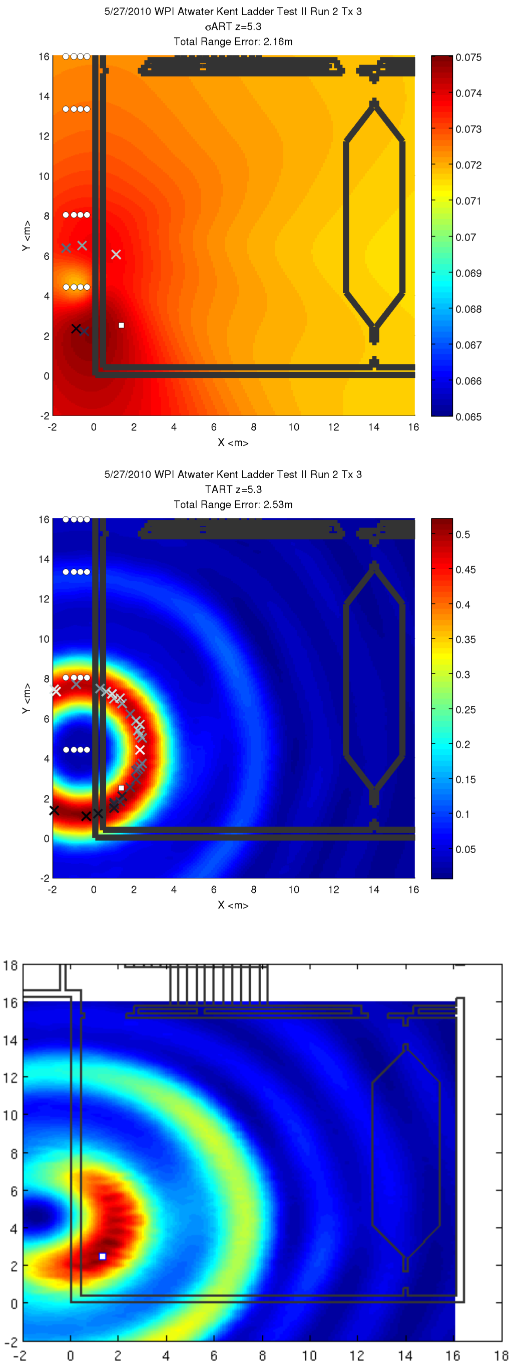

Fig. 10. Atwater Kent First Floor Point #12: sART (top), TART (middle), and Fusion (bottom) results

This paper has demonstrated that the information provided by the TART algorithm is complimentary to the information from the σART algorithm. These two algorithms do not provide us with measure of their confidence. The Bayesian Fusion Algorithm, however, can be rated according to the correlation between the underlying data sources. If the data sources are very highly correlated, it makes sense to trust the fused result, because all of the data are likely correct. If there is a relatively low degree of correlation then our assumptions of independence hold, and the fused solution should be an improvement over any of the individual data sources. When the correlation drops to near zero, we are in a situation where RF data alone cannot provide us with a reliable solution. Determining the thresholds for these regions of operation, and whether they vary with factors such as antenna geometry, or number of reference antennas will be addressed in future work. This self awareness of confidence makes this type of solution suitable for Kalman filtering, as well as fusion with additional data sources, such as inertial navigation data.

ACKNOWLEDGMENTS

The support of the Department of Homeland Security, U.S. Army Natick Soldier Research and Engineering Center and the Federal Emergency Management Agency is gratefully acknowledged.

REFERENCES

[1] A. Cavanaugh, M. Lowe, D. Cyganski, and R. J. Duckworth, " WPI Precision Personnel Location System: Rapid Deployment Antenna System and Supporting Algorithms for 3D Precision Location," in *ION International Technical Meeting*, Jan. 2010.

[2] J. Duckworth, D. Cyganski, S. Makarov, W. Michalson, J. Orr, V. Amendolare, J. Coyne, H. Daempfling, D. Hubelbank, H. Parikh, and B. Woodacre, "WPI precision personnel locator system: Evaluation by first responders," in *Proceedings of ION GNSS*, (Fort Worth, Texas), September 2007.

[3] V. T. Amendolare, *Transactional Array Reconcilliation Tomography for Precision Indoor Location*. PhD thesis, Worcester Polytechnic Institute, 2010.

[4] B. W. Woodacre, *Geometric Autoconfiguration for Precision Personnel Location*. PhD thesis, Worcester Polytechnic Institute, 2009.

[5] B. Woodacre, D. Cyganski, J. Duckworth, S. Makarov, W. Michalson, J. Orr, V. Amendolare, J. Coyne, and H. Daempfling, "WPI precision personnel locator system: Automatic antenna geometry estimation," in *Proceedings of the Institute of Navigation National Technical Meeting*, (San Diego, California), January 2008.

[6] V. Amendolare, D. Cyganski, and R. J. Duckworth, " WPI Precision Personnel Location System: Synchronization of Wireless Transceiver Units," in *JSDE/ION Joint Navigation Conference*, June 2009.

[7] A. Cavanaugh, "Bayesian Information Fusion for Precision Indoor Location," Master's thesis, Worcester Polytechnic Institute, 2010.

[8] V. Amendolare, "Synchronization in an Indoor Precision Location System," Master's thesis, Worcester Polytechnic Institute, 2007.

[9] M. C. Campbell, "Design of a Mobile Transceiver for Precision Indoor Location," Master's thesis, Worcester Polytechnic Institute, 2010.