Accurate Localization of RFID Tags Using Phase Difference

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***Abstract*—Due to their light weight, low power, and practically unlimited identification capacity, radio frequency identification (RFID) tags and associated devices offer distinctive advantages and are widely recognized for their promising potential in context-aware computing; by tagging objects with RFID tags, the environment can be sensed in a cost- and energy-efficient means. However, a prerequisite to fully realizing the potential is accurate localization of RFID tags, which will enable and enhance a wide range of applications. In this paper we show how to exploit the phase difference between two or more receiving antennas to compute accurate localization. Phase difference based localization has better accuracy, robustness and sensitivity when integrated with other measurements compared to the currently popular technique of localization using received signal strength. Using a software-defined radio setup, we show experimental results that support accurate localization of RFID tags and activity recognition based on phase difference.**

***Index Terms*—RFID localization, phase difference, maximum likelihood estimation, software-defined radio.**

I. Introduction

With the integration of computing into everyday objects and activities, ubiquitous computing has become part of our day to day lives. Due to the mobility and dynamic nature of the communication structure as well as the physical environment, ubiquitous computing has unique challenges and presents unprecedented opportunities [1], making context-aware computing a new paradigm. In this emerging context-aware computing, the applications adapt not only to the computing and communication constraints and resources, but also to the contextual information, such as the objects in the surroundings and people and activities in the vicinity, and even emotional and other states of the user [1]. To realize these potential improvements and make the context-aware applications cost-effective, the systems must be able to "sense" the environment effectively, with low energy and low cost [22], [21]. While traditional approaches such as vision-sensor and active sensor based methods are obvious choices for object recognition and localization [17], realization of a robust and cost-effective system based on these sensors has yet to be implemented after several decades of research.[1] Recent deployment of radio frequency identification (RFID) technology for efficient asset tracking and management has made RFID tags and associated devices widely available with low cost and low energy usage. For example, there are active RFID tags that typically last for five to seven years with a compact battery as a reliable wireless signal transmitter; obviously passive RFID tags have practically no lifetime limit. Clearly RFID tags, at a coarser level, provide a cost-effective and energy-efficient way of solving the environment sensing problem. One straightforward solution is to attach one or more RFID tags to each object of interest in the environment. As RFID tags have a limited range of readability, by reading all the tags in the proximity, using a reader or similar device, a computer can approximate its environment based on the sensed objects. Additionally, a unique advantage of RFID technology over vision and other sensor based methods is that RFID tags do not require line of sight in order to be "seen" and thus avoid problems associated with occlusion. Because of the unique and strategic advantages of RFID tags, they have been heavily investigated for numerous applications (e.g. [8], [17], [3], [16], [9], [15]).

While coarse-grained localization, that is, whether an object is present or absent in the proximity, is sufficient for many applications, a large number of applications will benefit from accurate location information of objects. For example, in a smart house setting, a low-cost solution of knowing precisely where people are and what objects are close to them will enable optimization of user interfaces and energy utilization and enhanced convenience. In addition, it is often important to track the motion of people/objects so that dynamic activities can be recognized and modeled. These applications have motivated numerous localization schemes and systems for RFID devices (see [5], [27] for recent reviews). Even though there are other schemes for localization such as using WiFi devices, WiFi devices are much larger in size and have much more strict power requirements, which makes RFID tags the most attractive choice for numerous applications.

In this paper, to achieve a fine-grained localization, we exploit the phase difference of the received signals at different antennas. While the received signal strength can attenuate quickly and therefore may lead to significant estimation errors of the location, the phase difference, on the other hand, can be estimated much more reliably as long as the signal-to-noise ratio is not too small. A unique advantage of the proposed phase difference method is that by measuring the phase difference between pulses within the same burst, one can estimate the motion of the object, thus making it feasible to monitor human activities at natural speeds. For example, our experiments suggest that we can reliably measure phase

[1]This does not imply that computer vision does not make any progress; on the contrary, computer vision has made numerous important breakthroughs.

difference within 0.57° (see Figs. 6 and 7). Another advantage of phase difference is that it can be combined with received-signal-strength-based scene analysis methods to improve the localization accuracy by using phase difference to estimate the local distance to reference tags.

To evaluate the effectiveness of phase difference for localization, we set up a plot study system that consists of active RFID tags, Universal Software Radio Peripheral (USRP) as receivers, and a pan-tilt unit to accurately place tags for various controlled experiments. Note that the model and the phase difference estimation methods apply to passive RFID tags in a similar manner[2]; here we limit our scope to active RFID tags, mainly so that our experiments are easy to replicate. The initial results we have are encouraging even though more localization experiments under real-world settings need to be further investigated.

The rest of the paper is organized as follows. Section II outlines the general localization problem and then reviews the related work on localization using RFID technology in the given framework by categorizing them based on several criteria. In Section III we describe the phase difference model and Section IV presents algorithms for phase difference estimation. Section V presents experimental results on localization and motion estimation and modeling. Section VI concludes the paper with a summary and discussion.

II. Related Work

The most general setup for RFID localization can be posted in a statistical inference framework [6], [14]. We represent the region of interest as a scene that consists of K RFID tags (wireless signal transmitters), whose configuration at time t is given by the location in the three dimensional space, the orientation of the transmitter's antenna, and the power level[3]; and N receivers, whose configuration is given similarly. Given a number of measurements between the tags and the receivers, the localization problem is to estimate the probability distribution of the location of the tags and receivers. Note that even though the localization algorithms developed for wireless ad-hoc networks and in particular, wireless sensor networks [14], can, in theory, be applied to localization using RFID technology, due to the unique characteristics of RFID technology, for example, no or very limited computation capabilities available on the tags, the potential large number of tags, and typical indoor operating environments; localization algorithms specific to RFIDs should be developed and studied [4].

The existing localization methods can be categorized based on 1) the constraints (i.e., range-free (based on connectivity information) or continuous measurements (such as received signal strength)), 2) the temporal nature of locations of tags and receivers (e.g., anchor-free or with reference tags or receivers at fixed locations), 3) and the statistical inference algorithm given the constraints. In the given setting, it is clear that range-free localization methods can be seen as a special case of using received signal strength, where only binary values of received signal strengths are available through reachability.

Before we summarize existing methods and systems for localization using RFID technology, we stress the significant differences between the results based only on computer simulations and the results based on physical system measurements. While RFID tags and readers are widely available, setting up an experimental system is not a straightforward task, as capturing wireless signals is full of challenges [23]. To avoid difficulties associated with prototyping, simulation is often used in various localization studies. For example, Wang et al. [20] propose an active scheme and passive scheme for RFID localization and provide supporting evidence through simulation in Matlab; Zhang et al. [25] propose the use of direction estimation for two dimensional localization; while they propose to use the phase difference to estimate the direction of arrival but they provide only simulation results. Bouet and Pujolle [4] use connectivity constraints through detectability of tags of mobile readers. While simulation results can be used to verify principles and theoretical aspects of localization and other methods, they are not sufficient to evaluate RFID localization performance as the wireless signals are affected by many other factors. Therefore, localization accuracy comparison between methods based on physical system measurements and methods based on simulation results (e.g. [4]) should be interpreted carefully.

Due to the difficulties of capturing and processing RFID communications, localization systems commonly rely on available wireless measurements at the receivers (e.g., RFID readers) such as received signal strength (RSS) (e.g., [11], [13]).[4] These RSS measurements can be binarized using some hardware or software threshold, resulting in binary readability/reachability values, which can be used as connectivity constraints in range-free localization systems. When the transmitting power of the transmitters can be dynamically changed, one can obtain a multi-level approximation of the range using multiple readability values [13]. This can be interpreted as an intermediate range representation between continuous values and range-free binary values. These measurements lead to constraints on the location and the orientation of tags as well as on the readers, which are then used by a statistical inference algorithm for localization. The localization step is often called the scene analysis step [5].

As the measurements and therefore constraints are pairwise between transmitters and receivers, they can be used to localize either transmitters or receivers using known fixed receivers or transmitters (called anchors), or both as in anchor-free systems. For example, SpotON [11] is based on RSS measurements estimated from adjustable sensors and the measurements

[2]For example, we can use one RFID reader to power and initiate wireless communications from passive tags.

[3]The power level of an active RFID tag is constant; for a passive tag, it can be changed by changing the power level of the reader.

[4]There are other measurements that can be used to estimate the distance, such as time difference of arrival [18] and time of arrival; these measurements are rarely used in RFID technology as these measurements are difficult and expensive to implement.

are used to estimate inter-tag distances with improved accuracy by calibrating radio signals to reduce the effects of hardware variability; as custom-built sensors used in SpotON are both transmitters and receivers, the system is more similar to a wireless ad-hoc network than to an RFID-based system. Landmarc [13] localizes RFID tags through comparing profiles with a number of reference tags with known locations; in this system nine readers with eight different power levels are used and a number of reference tags (i.e., tags with fixed and known location) are used for localization. To localize a tag, its estimated signal strengths from all the readers are compared to the corresponding measurements of reference tags. The estimated tag location is given by a weighted average of the k-nearest neighbors. The system is robust to some environmental factors as the reference and the unknown tags are subject to the same conditions; however, it is sensitive to tag orientation as the reference tags and the unknown tag can be oriented differently, specially when the tag is used to track moving objects. VIRE [26] uses the same localization method as in [13] and improves the efficiency of Landmarc by introducing a proximity map so that only tags in the neighboring areas need to be compared, rather than all the tags as in [13]. Zhang et al. [24] improves the localization accuracy of [13] by modeling the noise so that dissimilarity among tags is reduced for more reliable nearest neighbor matching and estimation. While the K nearest-neighbor estimation is commonly used as the inference algorithm, statistical inference algorithms are also used. For example, Bekkali et al. [2] propose to use Kalman filtering to estimate locations of unknown tags based on multilateration to the reference tags using two mobile RFID readers. A more general statistical inference framework is to use the Bayesian network [12] to estimate the locations and even orientation of tags and readers.

In this paper, we study the phase difference for accurate localization and motion tracking and activity recognition. In contrast to Zhang et al. [25], where phase difference is used only in simulations, our phase difference estimation is implemented and demonstrated using a prototype system and therefore our study is directly relevant to RFID applications that rely on localization. Our experiments show the phase difference can be estimated with high accuracy and can be used for three dimensional positioning. To the best of our knowledge, this is the first time that phase differences from RFID tags are measured reliably and are used for three dimensional positioning, motion estimation and tracking.

III. System Setup and Communication Model

In this paper, we focus on quantitative models of phase difference for RFID tags. The phase difference measurements are based on software-defined radios due to their flexibility in implementing various algorithms. To be more precise in presenting our model and algorithms, our formulation is based on the following setup we have. Clearly, for a different setup, the phase difference estimation algorithm and results should be similar even though changes may need to be made. As shown in Fig. 1, the system we have consists of RFID tags, a software-defined radio system, and a pan-tilt unit. The tags we use are the M100 asset tags from RF Code[5]. The carrier frequency of the tags is 433.92 MHz with typical transmission range over 90 meters (sufficient to cover entirely typical houses and offices). The tag uses the on-off keying (OOK) for communication, as it is simple to implement and is energy efficient (to prolong battery life). To meet the energy efficiency requirement, the signals are transmitted in a *burst* only at almost regular internals[6]. Using a compact battery (Lithium CR2032, which is replaceable), a tag typically lasts over seven years. During each burst, a fixed number of *pulses* are transmitted at seemingly the same magnitude with predetermined intervals, where we suspect that the lengths of the intervals are used to identify the tag. Each pulse is basically a sine wave for a short period of time on the carrier frequency.

Fig. 1. The system setup (consisting a software-defined radio (USRP), RFID tags, and a pan-tilt unit) we have used for accurate manipulation and placement of tags for controlled experiments.

To be able to implement various phase difference estimation algorithms and measure various aspects of the wireless communication, we have used software-defined radios for the experiments due to their flexibility[7]. The software-defined radios are based on the USRP from Ettus Research LLC[8], along with software modules and packages from the GNU software-defined ratio project[9]. We have used two RFX400 daughter boards, where both are configured as receivers. In order to estimate phase difference, the two receivers must be driven with the same sampling clock; otherwise, even a tiny mismatch between the clock will result in a huge phase difference. The USRP guarantees that the two channels are driven by the same sampling clock. In our system, the daughter boards are tuned to 433.92 MHz.

A. Communication Model

The wireless communication between the tags and the USRP unit is a typical wireless communication system and

[5]Specifications available from http://www.rfcode.com.
[6]The intervals are randomly perturbed for collision avoidance.
[7]Note the algorithms presented can be implemented in hardware efficiently if a hardware implementation is desired.
[8]http://www.ettus.com/.
[9]Available http://gnuradio.org.

here we follow the model in [19]. Based on our observation, the wireless signal from an RFID tag in one pulse can be described as $A\cos(2\pi f_c t)$, where A is the constant magnitude and f_c is the carrier frequency. At each daughter board, the received signal at its antenna is amplified and down-converted to the baseband. A baseband signal is represented by the inphase and quadrature components, denoted as $I(t)$ and $Q(t)$, respectively. If the carrier of the tag and the USRP are on exactly the same frequency, both $I(t)$ and $Q(t)$ should be a constant, depending only on the phase of the carriers. However, there will always be a frequency difference between the carrier of the tag and the carrier of the USRP due to the manufacturing process of the oscillator. Let f_r denote the frequency tuned to at the receivers. The waveforms at receiver 1 can be represented as

$$\begin{aligned} I_1(t) &= A_1\cos(2\pi(f_r - f_c)t + \phi_1) + \sigma_1 n_{11}, \\ Q_1(t) &= A_1\sin(2\pi(f_r - f_c)t + \phi_1) + \sigma_1 n_{12}, \end{aligned} \tag{1}$$

where A_1 is the received signal magnitude, ϕ_1 is the initial phase difference between the carrier at the tag and the carrier at the receiver, the initial carrier phase at the receiver, n_{11} and n_{12} are Gaussian noise terms of unit variance, and σ_1 is the noise level. Using similar notations, the waveforms at receiver 2 can be represented as

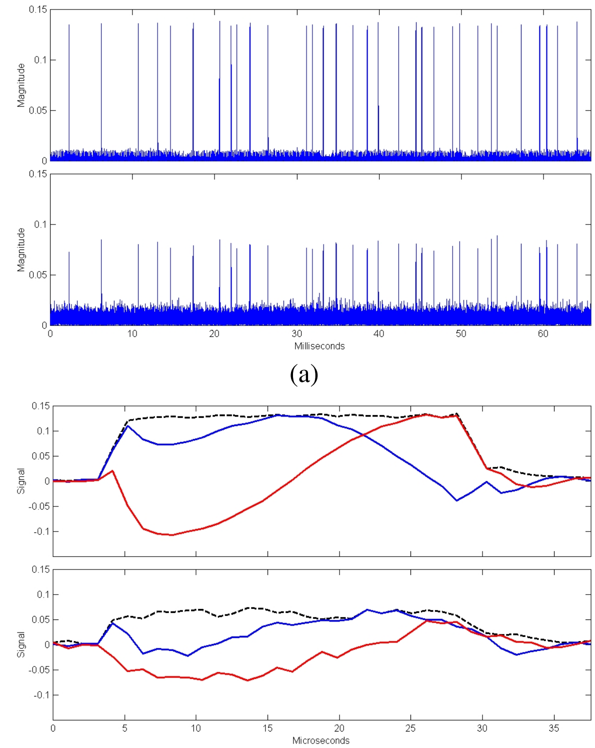
$$\begin{aligned} I_2(t) &= A_2\cos(2\pi(f_r - f_c)t + \phi_2) + \sigma_2 n_{21}, \\ Q_2(t) &= A_2\sin(2\pi(f_r - f_c)t + \phi_2) + \sigma_2 n_{22}. \end{aligned} \tag{2}$$

Wireless signals travel at the speed of light, such that ϕ_1 and ϕ_2 depend on the lengths of the paths from the tag to the receivers. However, the exact values of ϕ_1 and ϕ_2 also depend on the initialization process of the hardware, such that they cannot be used directly for distance and location estimation. Fortunately, the *phase difference*, i.e., $\phi_1 - \phi_2$, captures the difference of the distances of the paths, which can be used for location estimation.

B. Measured Waveforms and Phase Difference

To demonstrate that the wireless signals are reliable for phase difference estimation, Fig. 2 shows one burst received at the two antennas along with a zoomed version showing the signals during one pulse. These plots show clearly that the signals are robust and allow for reliable phase estimation and thus the phase difference estimation.

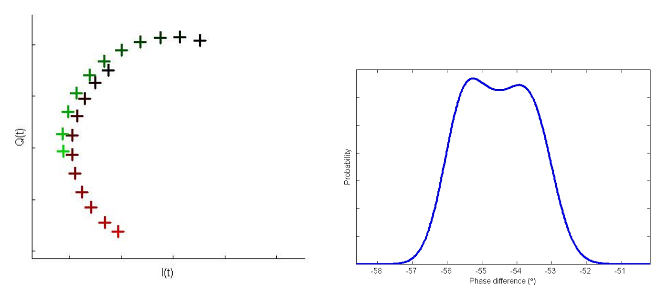
The waveforms received at the antennas as given in Eqs. (1) and (2) allow a straightforward estimation the phase difference. That is, at time t, the phase difference should be $\tan^{-1}(Q_1(t)/I_1(t)) - \tan^{-1}(Q_2(t)/I_2(t))$. Figure 3 shows one example of estimated phases during a pulse and a typical distribution of estimated phase difference during a burst. Figure 3(a) plots $I_1(t)$ v.s. $Q_1(t)$ (green '+') and $I_2(t)$ v.s. $Q_2(t)$ (red '+'); where the time is encoded by the intensity of the colors; it shows clearly the constant phase difference. Figure 3(b) shows the probability distribution of the phase differences of a stationary tag during one burst; here the probability distribution is estimated using the Parzen window method [10]. In this typical example, the standard deviation



(a)

(b)

Fig. 2. Waveforms received at antennas during a transmission of a burst. (a) Estimated magnitudes of the signals received at two antennas (top and bottom); (b) Each panel shows the received signals at an antenna, here the blue plot shows $I(t)$, and the red one shows $Q(t)$, and the black dashed one shows the magnitude $\sqrt{I(t)^2 + Q(t)^2}$.



(a) (b)

Fig. 3. Phase difference estimation example for one pulse. (a) The signals at two antennas, showing clearly the constant phase shift; (b) The estimated probability distribution of the estimated phase differences during a burst; here it is estimated using a Parzen window and the standard deviation of the distribution is 0.954°.

of the phase differences is 0.954°. For the waveforms at 433.92 MHz, this corresponds to a localization accuracy of 1.8 millimeters.[10] While the estimated accuracy is under an ideal situation, it shows clearly the feasibility of phase difference estimation for accurate localization.

IV. Maximum Likelihood Estimation of the Phase Difference

While the straightforward estimation the phase difference is often sufficient, for more reliable and accurate estimation in

[10]Given by $\frac{0.954}{360} \times \frac{299792458}{433920000}$ meter $= 0.0018$ meter, where 299792458 is the speed of light (meters/second).

cases such as phase difference tracking for moving RFID tags, one can use the maximum likelihood estimation. One option is to estimate the phase for each antenna separately and then compute the phase difference. The other option is to directly estimate the phase difference. In the first case, suppose we have n samples from the first antenna, $I_1(t_1), \dots, I_1(t_n)$, and $Q_1(t_1), \dots, Q_1(t_n)$. As the sampling rate of the channels is constant and known, we have $t_i = i \times \Delta t$, where Δt is given by the sampling rate.

Under the common assumption that the noise terms are statistically independent and follow the Gaussian distribution, we have

$$\begin{aligned} \widehat{\phi_1} &= \arg\max_{\phi_1} \prod_{i=1}^{i=n} (P(I_1(t_i)|\phi_1) \times P(Q_1(t_i)|\phi_1) \\ &= \arg\min_{\phi_1} \sum_{i=1}^{i=n} (I_1(t_i) - A_1 \cos(\Delta\omega \times i + \phi_1))^2 \\ &\quad + (Q_1(t_i) - A_1 \sin(\Delta\omega \times i + \phi_1))^2, \end{aligned} \tag{3}$$

where $\Delta\omega = 2\pi(f_r - f_c)\Delta t$. Here we assume that the original waveform is a pulse with a constant amplitude and therefore A_1 does not depend on i; we utilize the assumption that the $I_1(t_i) - A_1 \cos(\Delta\omega \times i + \phi_1)$ and $Q_1(t_i) - A_1 \sin(\Delta\omega \times i + \phi_1)$ are Gaussian distributed. This leads to a nonlinear optimization problem and it can be solved through a gradient method by initializing the variables with the mean estimation of the variables. For example, A_1 can be initialized with the average amplitude during the active pulse transmission.

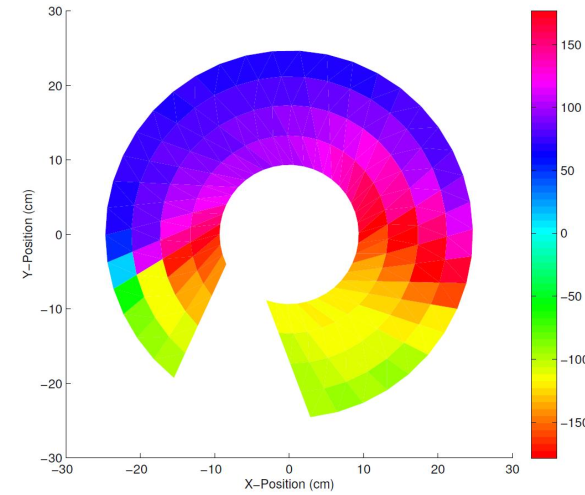
Note that the joint optimization of ϕ_1 and ϕ_2 can be done by weighting the criterion used in Eq. (3) by σ_1^2 and σ_2^2, which can be estimated using the channel signals when no pulses are being transmitted. We have implemented the maximum likelihood using a nonlinear optimization function in Matlab[11]. In typical waveforms, maximum likelihood estimation gives an improved phase difference estimation, even though the improvement is not always significant.

V. Experimental Results

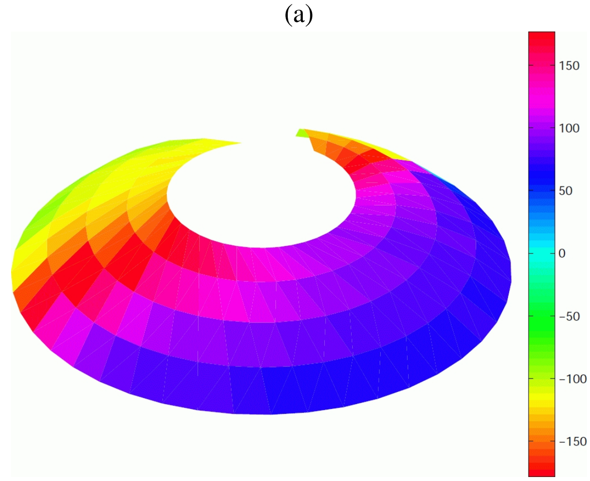
In this section we show the experimental results using the system setup outlined in Section II. In these experiments, we mount an RFID tag on the pan-tilt unit and set up the USRP unit with two receiving antennas tuned to 433.92 MHz; all the experiments were carried out in a room (roughly of 3.0m $\times$ 6.0m $\times$ 3.5m) with all the fixtures (desks, chairs, and books so on) in the room. While the set up we have may not be as realistic as in situations required by some applications, all the effects including multiple path, noise, and environment factors are intrinsically part of the measurements. Compared to simulation only studies (e.g. [20], [25]), our results are directly relevant and applicable to localization applications.

A critical test is whether the phase difference can be estimated reliably and whether the phase difference is discriminating, i.e., whether it changes smoothly when the tag is moved. Figure 4 shows one of the experiments that demonstrates these important features of the phase difference. In this experiment,

[11]We used fminsearch function; the Matlab is available from http://www.mathworks.com.



(a)

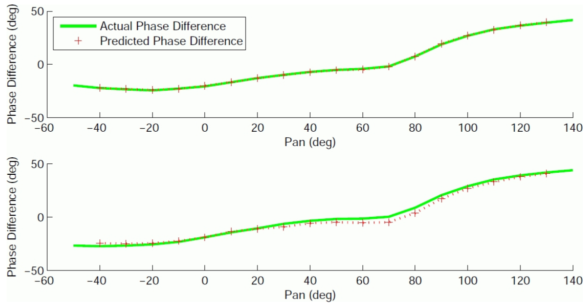


(b)

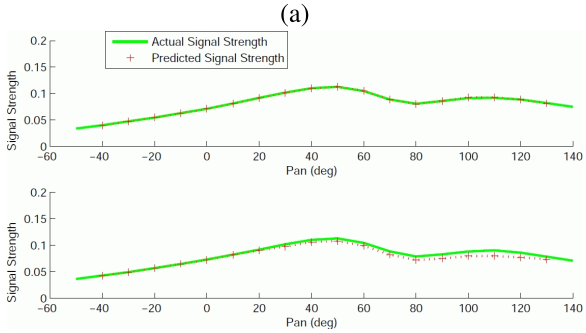
Fig. 4. Phase differences on a surface patch. (a) Top-down view; (b) side view to show the distribution in the three dimensional space.

we vary both the pan and tilt of the pan-tilt unit to cover a portion in the three dimensional space, which is similar to a portion of a sphere. For accurate measurements of phase difference, we systematically move the tag; at each location when the tag stops moving, we wait until we capture an active burst of pulses and then we move the tag to the next location. Figure 4 shows the phase difference on the surface; Fig. 4(a) gives a two-dimensional view of the surface to show the detailed variations and Fig. 4(b) shows a three-dimensional view. It is clear that the phase difference varies smoothly, depending on the three dimensional location of the tag. In other words, the phase difference provides information of the tag position in the three dimensional space.

Figure 5 shows a one-dimensional localization experiment. Due to an equipment constraint (as we have only one USRP unit with complete configurations), the localization is one dimensional. In these particular experiments, we demonstrate the localization accuracy based on profiling. Here we fix the tilt angle and change the pan from -130° to 70° with a 25° step size. For each run, we generate a profile as in [13], i.e., the phase differences along the path, and use the phase differences



(a)



(b)

Fig. 5. One dimensional localization experiments along an arc. Here two experiments are shown. (a) Prediction for phase difference; note that the absolute value of the phase difference is not essential as each USRP run gives a different systematic bias to the phases at the receivers; (b) Prediction for average signal strength at the two channels.

as training data. Then we collect test samples by starting from -117.5° with the same step size. We use the training profile to predict the values along the path by fitting the training samples to a spline and use the trained spline to predict the values at the test samples. To quantify the error between the prediction and the actual measurements, we define

$$e = \sqrt{\frac{1}{n}\frac{\sum_{i=1}^{n}(p(i)-a(i))^2}{var(a)}}, \tag{4}$$

where $p(i)$ and $a(i)$ are the predicted and actual values at location i, n is the total number of test locations, and $var(a)$ is the variance of the actual measurements. It is clear that the error given by Eq. (4) is unitless, and scale and translation invariant. Figure 5(a) shows two different experiments and standard deviation between the predicted and actual phase difference values is 0.34° and 2.3° respectively; the error according to Eq. (4) is 0.02 and 0.12 for the top and the bottom experiment respectively. These examples show clearly that phase difference is a reliable measurement of the difference in distances from the antennas to the tag, allowing for millimeter accuracy prediction. To compare with received signal strength estimation, Fig. 5(b) shows the corresponding plots for the average RSS from the antennas. Here the error according to Eq. (4) is 0.02 and 0.28 respectively. While both phase difference and RSS are reliable with small error, this result show that when the signal to noise ratio is lower, the error for RSS tends to be larger.

Figure 6 demonstrates a unique advantage of phase difference. As phase differences change with small changes in distance, they can be used to estimate motion and can then be used in human activity recognition. In these experiments, we move the mounted tag with a constant pan motion while we capture the wireless signals; the moving speed is roughly 1.3 meters per second, corresponding to a typical human walking speed. Note that we do not stop the tag to acquire data as in the previous experiments. Here we estimate the phase difference using the samples within each pulse; the pulses are detected based on a threshold of the magnitude above a constant factor of the noise level, that is estimated automatically. The plots in Fig. 6(a)-(c) shows the estimated phase difference during a burst while the tag is in motion; Fig. 6(d) shows the phase difference when the tag is static for comparison. These plots show interesting patterns and may lead to new and efficient ways of modeling activities. In the three examples when the tag is moving, the phase difference changes smoothly in all the three cases, but with different changing patterns. Additionally, these plots show the phase difference can be estimated accurately and reliably even when the tags are moving. The results show again the accuracy of estimated phase difference and the sensitivity of the phase difference relative to the motion.

For comparison, Fig. 7 shows the received signal strength corresponding to the two cases in Fig. 6(a) and (b). While received signal strength does also change, it does not show as large changes as the phase difference. Additionally, the patterns of changes are much similar, compared to the phase difference ones. These experiments suggest that phase difference would be more effective for activity characterization and recognition.

VI. Conclusion

In this paper we exploit the phase difference between two receiving antennas for localization. Using a software defined radio implementation, we demonstrate that phase difference can be estimated reliably for commercially available RFID tags and they can be used for localization in three dimensional and for motion estimation and tracking. The experiments demonstrate clearly the advantages of phase difference for accurate localization. The experiments show millimeter accuracy localization is achievable under ideal situations. While in more realistic settings, the performance may degrade and but we expect the results should be robust. While further experiments are needed for complete evaluation, the results show clearly the potential usefulness of phase difference. For motion estimation and recognition, the phase difference may provide a unique method to achieve energy efficient motion estimation. Additionally, the phase difference estimation can be directly integrated with RSS based methods to improve the local estimation or to reduce the number of reference tags required. Given all the experiments reported, the next logical step is to implement a full localization system using several USRP units for three dimensional localization and evaluate the accuracy of the approach.

As the system we have consists of a software-defined radio component for its flexibility to set up and test various algo-

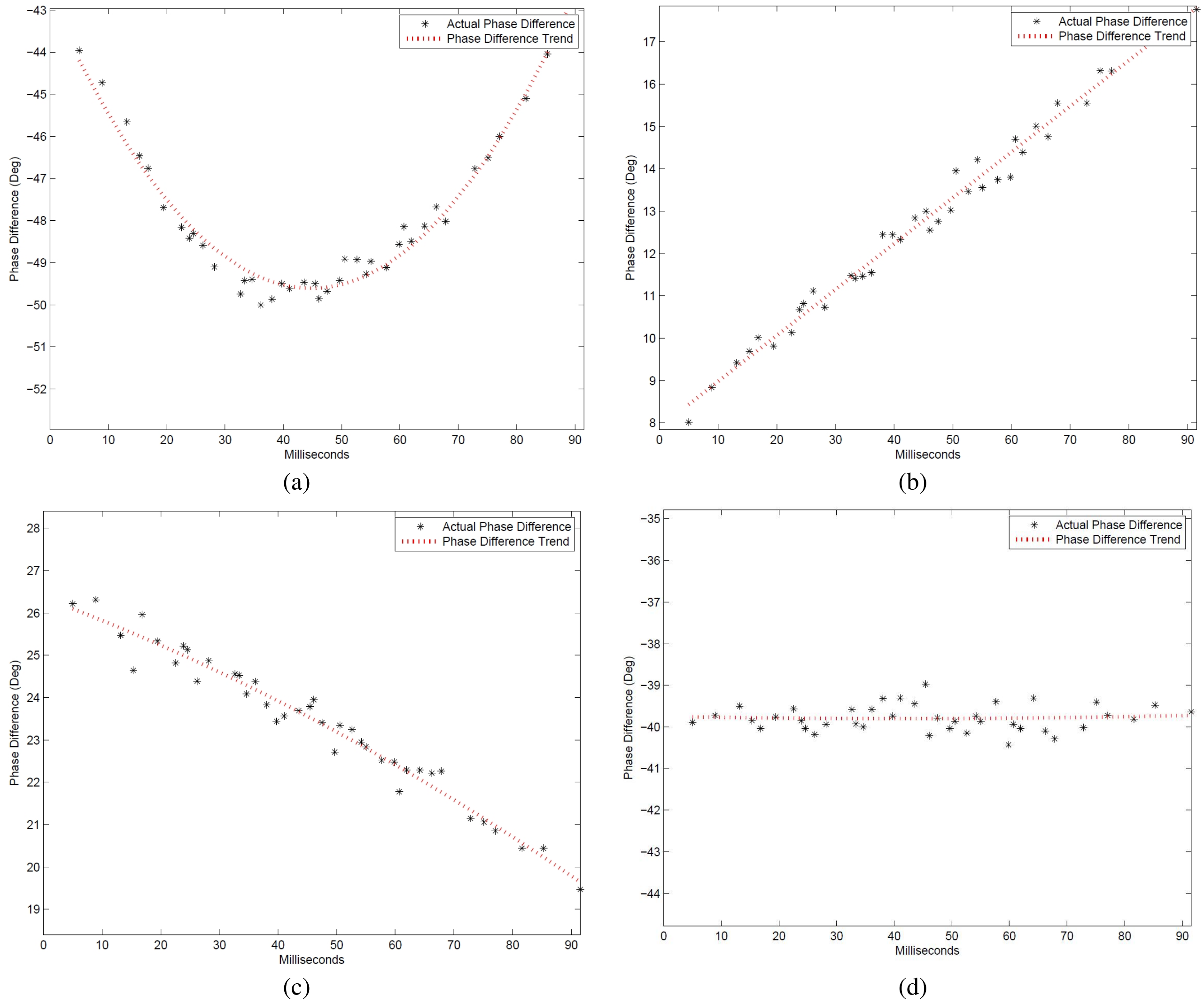


Fig. 6. Three examples ((a)-(c)) of phase differences estimated during pulses within a burst when the tag is moving; for comparison, (d) shows the phase difference when the same tag is static.

rithms, one potential issue is the complexity of the algorithms when a hardware system needs to be realized. The phase difference algorithm can clearly be streamlined and so its implementation should not require special parts beyond typical digital signal processing components.

Based on the experimental results, estimated phase differences can be used in a number of applications to improve the localization accuracy. For example, for searching book in library, high localization accuracy is needed to make the RFID techniques effective [9]. Combined with other coarser level localization, phase difference may provide the millimeter localization accuracy when books to be interested are known to be an area; this is being investigated further. For robot navigation, robots need to sense their environment and require accurate localization of obstacles and other objects and estimated phase difference may achieve the required accuracy that is otherwise not feasible using the RFID technology.

There are several improvements that can be made. One of the key questions is how sensitive the phase difference estimation is with respect to other factors such as multi-path problems and orientation. For certain applications, the phase difference will allow us to track and model motions of people and other moving objects, which provide information to estimate the underlying three dimensional structure of the environment, and thus a ray-tracing based method may be used to approximate multi-path problems. It is often reported that RFID tags are sensitive to orientation of the tags relative to the receivers due to the size of the antenna and other physical constraints of the tags. It appears that the phase difference may be more robust to orientation changes. Figure 8 shows an experiment where we rotate the tags. Clearly the orientation sensitivity has an intrinsic structure and is relative invariant under certain conditions. A complete understanding of orientation sensitivity under realistic scenarios is required; for certain applications, the increasingly available computational RFID tags [7] can be used, which can estimate and report their orientation using built-in programs and accelerometers.

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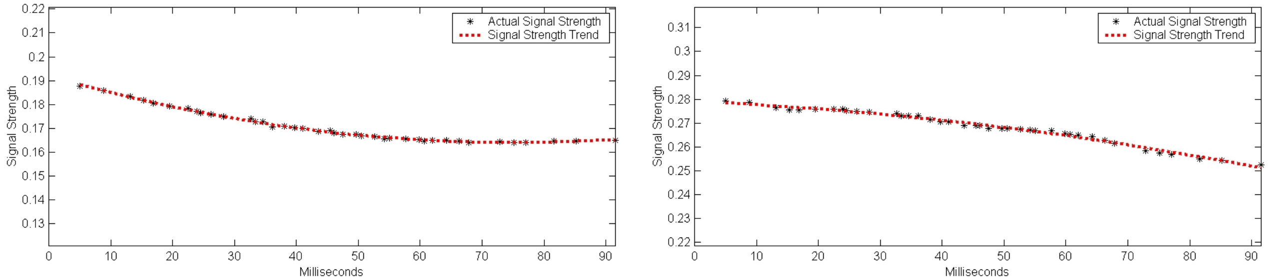

Fig. 7. The received signal strength plots corresponding to the two cases shown in 6 (a) and (b).

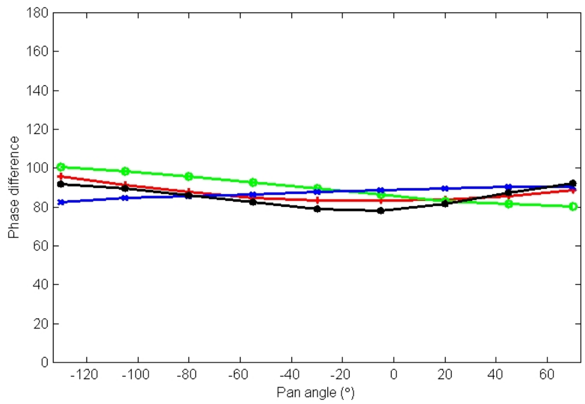

Fig. 8. The phase difference of four different orientations along an arc generated by panning the tag.

REFERENCES

[1] Frank Adelstein, Sandeep KS Gupta, Golden Richard III, and Loren Schwiebert. *fundamentals of Mobile and Pervasive Computing*. McGraw-Hill, 2005.

[2] Abdelmoula Bekkali, Horacio Sanson, and Mitsuji Matsumoto. Rfid indoor positioning based on probabilistic rfid map and kalman filtering. In *Proceedings of the IEEE International Conference on Wireless and Mobile Computing, Networking and Communication,*, pages 21–27, 2007.

[3] Gaetano Borriello, Waylon Brunette, Matthew Hall, Carl Hartung, and Cameron Tangney. Reminding about tagged objects using passive rfids. In *Proceedings of the International Conference on Ubiquitous Computing*, 2004.

[4] M. Bouet and G. Pujolle. L-virt: Range-free 3-d localization of rfid tags based on topological constraints. *Computer Communications*, 32:1485–1494, 2009.

[5] Mathieu Bouet, Aldri L. dos Santos, and Guy Pujolle. Rfid tags: Positioning principles and localization techniques. In *Proceedings of IFIP Wireless Days - 2nd International Home Networking Conference (IHN 2008)*, November 2008.

[6] Mauro Brunato and Roberto Battiti. Statistical learning theory for location fingerprinting in wireless lans. *Computer Networks*, 47(6):825–845, 2005.

[7] Michael Buettner, Richa Prasad, Matthai Philipose, and David Wetherall. Recognizing daily activities with rfid-based sensors. In *Proc. 11th International Conference on Ubiquitous Computing (UbiComp)*, Orlando, Florida, USA, October 2009.

[8] Tzung-Shi Chen, Cheng-Sian Chang, Jeng-Shian Lin, and Hui-Ling Yu. Context-aware writing in ubiquitous learning environments. In *Proceedings of the Fifth IEEE International Conference on Wireless, Mobile, and Ubiquitous Technology in Education*, pages 67–73, 2008.

[9] Jung-Wook Choi, Dong-Ik Oh, and Il-Yeol Song. R-lim: an affordable library search system based on rfid. In *Proceedings of the International Conference on Hybrid Information Technology*, volume 1, pages 103–108, 2006.

[10] Richard O. Duda, Peter E. Hart, and David G. Stork. *Pattern Classification*. Wiley-Interscience, 2000.

[11] Jeffrey Hightower, Chris Vakili, Gaetano Borriello, and Roy Want. Design and calibration of the spoton ad-hoc location sensing system. In *Technical Report, Department of Computer Science, University of Washington*, August 2001.

[12] David Madigan, Eiman Elnahrawy, Richard P. Martin, Wen-Hua Ju, P. Krishnan, and A. S. Krishnakumar. Bayesian indoor positioning systems. In *Proceedings of the Annual Joint Conference of the IEEE Computer and Communications Societies*, volume 2, pages 1217–1227, 2005.

[13] Lionel M Ni, Yunhao Liu, Yiu Cho Lau, and Abhishek Patil. Landmarc: Indoor location sensing using active rfid. *Wireless Networks*, 10(6):701–710, 2004.

[14] Rong Peng and Mihail L. Sichitiu. Probabilistic localization for outdoor wireless sensor networks. *ACM Mobile Computing and Communications Review*, 11(1):53–64, 2007.

[15] Lenin Ravindranath, Venkata N. Padmanabhan, and Piyush Agrawal. Sixthsense: Rfid-based enterprise intelligence. In *Proceeding of the International Conference on Mobile systems, applications, and services*, pages 253–266, 2008.

[16] S. Schneegans, P. Vorst, and A. Zell. Using rfid snapshots for mobile robot self-localization. In *Proceedings of the European Conference on Mobile Robots*, pages 241–246, 2007.

[17] J. R. Smith, K. P. Fishkin, B. Jiang, A. Mamishev, M. Philipose, Rea A, D, S. Roy, and K. Sundara-Rajan. Rfid-based techniques for human-activity detection. *Commun. ACM*, 48(9):39–44, 2005.

[18] A. Stelzer, K. Pourvoyeur, and A. Fischer. Concept and application of lpm - a novel 3-d local position measurement system. *IEEE Transactions on Microwave Theory and Techniques*, 52(12):2664–2669, 2004.

[19] D. Tse and P. Viswanath. *Fundamentals of wireless communication*. Cambridge Univ Pr, 2005.

[20] C. Wang, H. Wu, and N.F. Tzeng. RFID-based 3-D positioning schemes. In *Proceedings of the Annual Joint Conference of the IEEE Computer and Communications Societies*, pages 1235–1243, 2007.

[21] Fusheng Wang, Shaorong Liu, Peiya Liu, and Yijian Bai. Bridging physical and virtual worlds : Complex event processing for rfid data streams. In *Proceedings of the International Conference on Extending Database Technology*, 2006.

[22] Roy Want, Kenneth P. Fishkin, Anuj Gujar, and Beverly L. Harrison. Bridging physical and virtual worlds with electronic tags. In *Proceedings of the SIGCHI conference on Human factors in computing systems*, pages 370–377, New York, NY, USA, 1999. ACM.

[23] Evan Welbourne, Magdalena Balazinska, Gaetano Borriello, and Waylon Brunette. Challenges for pervasive rfid-based infrastructures. In *Proceedings of the IEEE International Conference on Pervasive Computing and Communications Workshops*, pages 388–394, 2007.

[24] Ting Zhang, Zhenyong Chen, Yuanxin Ouyang, Jiuyue Hao, and Zhang Xiong. An improved rfid-based locating algorithm by eliminating diversity of active tags for indoor environment. *he Computer Journal*, 52(8):902–909, 2009.

[25] Yimin Zhang, Moeness G. Amin, and Shashank Kaushik. Localization and Tracking of Passive RFID Tags Based on Direction Estimation. *International Journal of Antennas and Propagation*, 2007.

[26] Y. Zhao, Y. Liu, and L.M. Ni. Vire: Active rfid-based localization using virtual reference elimination. In *Proceedings of ICPP*, 2007.

[27] J. Zhou and J. Shi. RFID localization algorithms and applications, a review. *Journal of Intelligent Manufacturing*, pages 1–13, 2008.