Design an Asynchronous Radio Interferometric Positioning System Using Dual-Tone Signaling

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***Abstract*—Radio interferometric positioning systems (RIPS) are recently proposed for low-complexity and high-accuracy localization. However, the original RIPS involves four nodes (two transmitters and two receivers) for a ranging session, and requires stringent time synchronization upon two receivers. In this paper, an asynchronous radio interferometric positioning system (ARIPS) is developed with larger positioning ranges. In ARIPS, two anchors (nodes with known positions) transmit two slightly different dual-tone signals. The differences of the two dual-tone signals create two low-frequency differential signals at the target receiver. The phase differences of the differential signals bear the time-difference-of-arrival (TDOA) information, i.e., the distance information. We develop two new methods to estimate the TDOA with and without accurate knowledge of the frequencies of the differential signals, respectively. By switching the pairs of the anchor nodes, several TDOAs can be obtained and thus the location of the target node can be estimated. The proposed ARIPS is robust to carrier frequency offsets (CFOs) and random phases due to asynchronous oscillators, and increases the resolving range limit due to the well-known integer ambiguity issue. Simulation results illustrate the performance of the proposed ARIPS.**

***Index Terms*—Ranging, sensor networks, synchronization, time-difference-of-arrival, radio interferometry, localization**

I. Introduction

Localization-awareness is crucial for wireless sensor networks (WSNs) [1], [2], since the data collected by sensors should be stamped with their corresponding locations. Numerous applications of WSNs require accurate location information, such as target tracking, environment monitoring, search and rescue etc. The low-power and low-cost constraints of sensor nodes impose great challenges on the development of low-complexity localization strategies. Meanwhile, the high-accuracy requirement further increases the localization difficulties. Although the distinguish properties of ultra-wideband (UWB) impulse radio (IR) [3], [4] enable time-based localization with high accuracy, the prohibitively high Nyquist sampling rate of UWB systems discourages their popularity. Therefore, to increase the accuracy of localization systems using narrowband signals is still of great interest considering implementation cost.

A low-complexity radio interferometric positioning system (RIPS) is proposed in [5] to achieve both high accuracy and large positioning area. In principle, the RIPS estimates the phase of a low-frequency differential signal produced by two sinusoid signals with slightly different frequencies, where the phase is related to the range information. The RIPS requires time synchronization of two receivers and faces the integer ambiguity issue. Furthermore, its output Q-range (a linear combination of four distances) needs special localization algorithm. The RIPS is extended in [6], [7] to track mobile nodes, where Doppler shifts are further explored and velocity estimates of moving targets are achieved. Moreover, spinning beacons are employed in [8] to produce specified Doppler signals, and then angle-of-arrivals (AOAs) are estimated as localization metrics. A received signal strength (RSS) based ranging method is proposed in [9], which takes multipath parameters into the RSS model. By measuring the RSS of different spectrum channels, it collects enough data to estimate all the unknown multipath parameters. All the above examples show the efforts to improve localization accuracy using narrowband signals.

In this paper, we propose an asynchronous radio interferometric positioning system (ARIPS) using dual-tone signals. Two anchors (nodes with known positions) transmit dual-tone signals, whose frequencies are slightly different from each other. At the target receiver, two low-frequency differential signals are created by a simple square-law device and a low-pass filter (LPF). The phases of these signals contain delay information between the two transmitters and the receiver. By extracting the phase difference, we can recover the time-difference-of-arrival (TDOA). Repeating this ranging procedure, we obtain several TDOAs of different anchor-target pairs. Conventional TDOA-based localization algorithms [10], [11] can be applied directly. Our proposed method has several advantages: i) carrier frequency offsets and random phases due to asynchronous oscillators are accommodated; ii) increasing the resolving range limit due to the integer ambiguity issue; and iii) the TDOA estimate result is much easier to use compared to the Q-range obtained by the RIPS [5].

The rest of the paper is organized as follows. In Section II, system model is introduced. The ARIPS using dual-tone ranging method is proposed in Section III. We consider the cases with and without accurate knowledge of the differential frequency, respectively. The simulation results are shown in Section IV. We draw the conclusions at the end of this paper.

II. System Model

Let us consider a single target scenario where two anchor nodes transmit dual-tone signals, and a target node receives

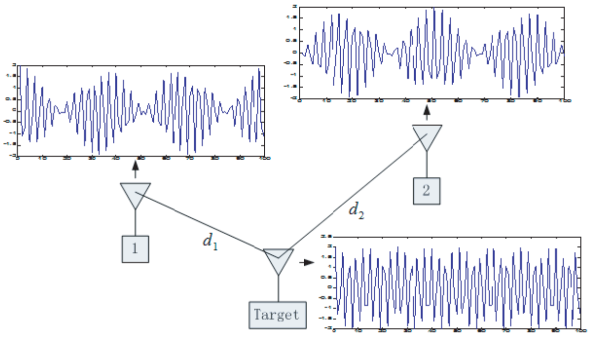

Fig. 1. The dual-tone ranging method

these signals via different delays as shown in Fig. 1. This can be easily extended to multi-target scenarios, where several target nodes receive the broadcast dual-tone signals by anchors. Without loss of generality, we model the dual-tone signals transmitted by Node 1 and Node 2 respectively as

$$\begin{aligned} s_1(t) &= a_1\cos(2\pi f_c t + \phi_1) \\ &\quad + b_1\cos(2\pi(f_c + f_d)t + \phi_1), \qquad (1) \\ s_2(t) &= a_2\cos(2\pi(f_c + f_o)t + \phi_2) \\ &\quad + b_2\cos(2\pi(f_c + f_d + 2f_o)t + \phi_2), \qquad (2) \end{aligned}$$

where f_c is the carrier frequency, f_d is the frequency difference between the first and the second tones of Node 1, f_o is the differential frequency and can be viewed as an intentional frequency offset as well, ϕ_1 (or ϕ_2) denotes the randomness of the oscillator of Node 1 (or Node 2), and a_1 and b_1 (or a_2 and b_2) are the amplitudes of the transmitted tones of Node 1 (or Node 2). Since each dual-tone signal is generated by a single node, the phase offset is the same for both tones. We remark that the carrier frequencies of Node 1 and Node 2 may be different due to asynchronous oscillators. We will address the effect of the carrier frequency offset (CFO) later. The asynchronization in the ARIPS refers to the effects caused by the CFO and random phases.

Through additive white Gaussian noise (AWGN) channels, the received signal at the target node can be modeled as

$$r(t) = s_1(t - \tau_1) + s_2(t - \tau_2) + n(t), \qquad (3)$$

where τ_1 and τ_2 are the transmission delays from Node 1 and Node 2 to the target node, respectively, and $n(t)$ represents the AWGN. The delays are in the linear relation to the distances as $d_i = c\tau_i, i = 1, 2$, where c is the signal propagation speed (Here $c = 3 \times 10^8$ m/s the speed of light) and d_i is the distance between the ith node and the target node. Note that time synchronization is assumed here.

III. The ARIPS using Dual-tone Ranging Method

A. With accurate knowledge of f_o

In order to obtain low-frequency differential signals, we let $r(t)$ go through a square-law device. Hence, $r^2(t)$ can be written as

$$\begin{aligned} r^2(t) &= s_1^2(t - \tau_1) + s_2^2(t - \tau_2) \\ &\quad + 2s_1(t - \tau_1)s_2(t - \tau_2) + m(t), \end{aligned} \qquad (4)$$

where $m(t) = n^2(t) + 2n(t)(s_1(t - \tau_1) + s_2(t - \tau_2))$, and $s_1^2(t - \tau_1) = (a_1^2 + b_1^2)/2 + v(t)$ with $v(t)$ including 8 frequency components of $\pm 2f_c, \pm(2f_c+2f_d), \pm(2f_c+f_d)$, and $\pm f_d$. Moreover, $s_2^2(t - \tau_2)$ contains the DC and 8 frequency components of $\pm(2f_c + 2f_o), \pm(2f_c + 2f_d + 4f_o), \pm(2f_c + f_d + 3f_o)$, and $\pm(f_d + f_o)$. Now let us investigate the cross term $s_1(t-\tau_1)s_2(t-\tau_2)$. Defining $\tau_{12} = \tau_1 - \tau_2$, $\theta_0 = f_c\tau_{12}$, $\theta_1 = -f_o\tau_2$ and $\theta = f_d\tau_{12} - f_o\tau_2$, we write the cross term $2s_1(t - \tau_1)s_2(t - \tau_2)$ as

$$\begin{aligned} & 2s_1(t - \tau_1)s_2(t - \tau_2) \qquad (5) \\ = \; & a_1a_2\cos(2\pi(f_o t + \theta_0 + \theta_1) + \phi_1 - \phi_2) \\ & + b_1b_2\cos(2\pi(2f_o t + \theta_0 + \theta_1 + \theta) + \phi_1 - \phi_2) + u(t), \end{aligned}$$

where $u(t)$ contains in total 12 frequency components of $\pm(2f_c + f_o), \pm(2f_c + f_d + 2f_o), \pm(2f_c + f_d + f_o), \pm(2f_c + 2f_d + 2f_o), \pm(f_d + 2f_o)$, and $\pm(f_d - f_o)$. Furthermore, we assume $f_c \gg f_d$ and $f_d \gg 3f_o$. Therefore, $r^2(t)$ includes 4 low-frequency and other moderate- and high-frequency components as well. If we employ an LPF to get rid of all the frequency components beyond $2f_o$, we achieve 4 low-frequency components, whose phases bear the delay information. Excluding the DC component, we model the output of the LPF as

$$\begin{aligned} \widetilde{r}(t) &= a_1a_2\cos(2\pi(f_o t + \theta_0 + \theta_1) + \phi_1 - \phi_2) \qquad (6) \\ &\quad + b_1b_2\cos(2\pi(2f_o t + \theta_0 + \theta_1 + \theta) + \phi_1 - \phi_2) + \widetilde{m}(t), \end{aligned}$$

where $\widetilde{m}(t)$ indicates the aggregate noise term, which includes the noise and the residuals of moderate- and high-frequency components through the LPF. Note that $r^2(t)$ includes in total 32 frequency components, but only 4 low-frequency components included in $\widetilde{r}(t)$ are used to extract the delay information.

Let us sample $\widetilde{r}(t)$ by a sampling rate $1/T_s$ which is no less than the Nyquist sampling rate ($1/T_s \geq 4f_o$), and collect all N samples into a vector $\widetilde{\mathbf{r}}$. Thus, $\widetilde{\mathbf{r}}$ can be modeled as

$$\widetilde{\mathbf{r}} = \mathbf{H}_N(f_o)\mathbf{x} + \widetilde{\mathbf{m}}, \qquad (7)$$

where $\widetilde{\mathbf{m}}$ is the sample vector of $\widetilde{m}(t)$, and $\mathbf{x} = [\alpha, \beta, \alpha^*, \beta^*]^T$ with $\alpha = a_1a_2e^{j2\pi(\theta_0+\theta_1)+j(\phi_1-\phi_2)}$, $\beta = b_1b_2e^{j2\pi(\theta_0+\theta_1+\theta)+j(\phi_1-\phi_2)}$, and α^* (or β^*) is the complex conjugate of α (or β). Furthermore, $\mathbf{H}_N(f_o) = [\mathbf{h}_N(f_o)\ \mathbf{h}_N(2f_o)\ \mathbf{h}_N(-f_o)\ \mathbf{h}_N(-2f_o)]$ with $\mathbf{h}_N(f) = [1, e^{j2\pi fT_s}, e^{j2\pi 2fT_s}, \ldots, e^{j2\pi(N-1)fT_s}]^T$. Assuming the accurate knowledge of f_o, we can estimate $\mathbf{x}$ by a least-squares (LS) estimator as

$$\hat{\mathbf{x}} = \mathbf{H}_N^{\dagger}(f_o)\widetilde{\mathbf{r}}. \qquad (8)$$

Note that by extracting the phase information of $\hat{\mathbf{x}}$, we can only estimate $\widetilde{\theta}$ instead of θ, where $\widetilde{\theta} = \theta - k$ with $k = \lfloor \theta \rfloor$. This is the well-known integer ambiguity issue due to the unknown integer k [12]. We will discuss it later. An estimator of $\widetilde{\theta}$ is given by

$$\hat{\widetilde{\theta}} = \frac{1}{2\pi}\arg([\hat{\mathbf{x}}]_2[\hat{\mathbf{x}}]_3 + [\hat{\mathbf{x}}]_1^*[\hat{\mathbf{x}}]_4^*). \quad (9)$$

Now let us extract the delay information from the phase estimate. We decompose θ as

$$\begin{aligned}\theta &= f_d\tau_{12} - f_o\tau_2 \\ &= (f_d + f_o/2)\tau_{12} - (f_o/2)\eta_{12},\end{aligned} \quad (10)$$

where τ_{12} denoting the TDOA, and $\eta_{12} = \tau_1 + \tau_2$ representing the summation of the delays. Recalling that $f_d \gg 3f_o$, we arrive at

$$\begin{cases} \theta \approx (f_d + f_o/2)\tau_{12}, & \tau_1 \neq \tau_2 \\ \theta = -f_o\tau_2 & \tau_1 = \tau_2 \end{cases}. \quad (11)$$

When $\tau_1 \neq \tau_2$, θ is approximately in a linear relation to τ_{12} and $-(f_o/2)\eta_{12}$ is the approximation error. Thus, we obtain an estimate of τ_{12} as

$$\hat{\tau}_{12} = (\hat{\widetilde{\theta}} + k)/(f_d + f_o/2), \quad (12)$$

where the unknown k counts for the integer ambiguity. When $\tau_1 = \tau_2$, we achieve $\hat{\tau}_{12} \approx 0$ with the condition of $f_d \gg 3f_o$. Therefore, $\hat{\tau}_{12}$ (12) can be used as a general estimator of τ_{12}. The following remarks are in order.

Remark 1: The unknown phase offsets ϕ_1 and ϕ_2 do not have any impact on the TDOA estimation, as they are eliminated elegantly in our estimation method. Therefore, the proposed ARIPS is robust to random phase offsets.

Remark 2: The unknown θ_0 as the product of the basis frequency f_c and the TDOA τ_{12} is canceled as well. The only requirement to design f_c is that $f_c \gg f_d$. We can choose f_c for easy implementation.

Remark 3: The TDOA is a more favorable metric as the input of localization algorithms than the Q-range of the RIPS. Several TDOAs can be estimated in the same way between different anchor-target pairs. Thus, various localization algorithms based on TDOAs [10], [11] can be directly applied.

Remark 4: We only use dual-tone instead of multi-tone signals, as the number of nuisance frequency components increases quadratically with the number of tones. The benefit of using multi-tone signals to obtain extra information is not worthwhile for the loss of the transmission efficiency.

Remark 5: When $|\theta| < 1/2$, we achieve $\widetilde{\theta} = \theta$ and $k = 0$. The estimate of τ_{12} is simplified as

$$\hat{\tau}_{12} = \hat{\widetilde{\theta}}/(f_d + f_o/2), \quad (13)$$

where is no integer ambiguity issue. Hence, we are able to resolve $|\tau_{12}|$ in the range of $[0, 1/(2f_d + f_o)]$ without integer ambiguity. Therefore, we can design f_d and f_o according to the range of interest. For example, the distances of interest are limited to a few hundreds meters or less than 1 km. Thus, $|c\tau_{12}| \leq 1$ km and $0 \leq c\eta_{12} \leq 2$ km. In order to avoid the integer ambiguity, we should choose f_d to be smaller than 150 KHz. Since $f_d \gg 3f_o$ (50 KHz $\gg f_o$) and $1 \gg f_o\eta_{12}$ (150 KHz $\gg f_o$), we can design $f_o < 1$ KHz. These conditions are not difficult to fulfill. As a result, the approximation error of the phase model (11) is smaller than 0.0033. The freedom to design f_d and f_o increases the resolving range limit of the proposed ARIPS. Note that in the ARIPS, we are able to design three parameters f_c, f_d and f_o to determine the transmitted dual-tone signals. The ARIPS is more flexible in dealing with the integer ambiguity compared to the RIPS, where $\theta_{RIPS} \approx Q_{rang}(f_1 + f_2)/2c \mod 1$, with f_1 and f_2 transmitted frequencies by Node 1 and Node 2, respectively. Thus, the RIPS can resolve the $|Q_{rang}|$ in the range of $[0, c/(f_1 + f_2)]$. If we still assume the distances are less than 1 km, the frequencies of transmitted signals (f_1 and f_2) in the RIPS cannot be larger than 75 KHz in order to avoid the integer ambiguity issue.

Remark 6: The disadvantage for both the ARIPS and the RIPS is that they are not robust to multipath channels. The phase information will be contaminated by the unknown multipath channel. One possible approach to solve this problem is to repeatedly measure the same TDOA using different dual-tone signals [6], [9]. We model each multipath component using an amplitude and a delay, and bound the number of multipaths. By collecting enough measurements, we can estimate all the unknown parameters. This is similar to recover the channel impulse response in the frequency domain [13].

B. Without accurate knowledge of f_o

According to (7), we inverse $\mathbf{H}_N(f_o)$ with the accurate knowledge of f_o and obtain the estimate of $\mathbf{x}$ as (8). However, we may not have the accurate knowledge of f_o due to various reasons, such as low-cost oscillators and unreliable sensor nodes. Furthermore, the CFO between transmitters could be one of the reasons as well. The actual f_o would be the sum of the nominated f_o and the unknown CFO. Therefore, we have to estimate f_o to construct $\mathbf{H}_N(f_o)$ accordingly, and then estimate $\mathbf{x}$.

For simplicity, we ignore the noise term from now on. The sample vector $\widetilde{\mathbf{r}}$ is rearranged into a matrix $\mathbf{R}$ of size $p \times q$ with $q = N - p + 1$ as

$$\mathbf{R} = \left[\begin{array}{ccccc} [\widetilde{\mathbf{r}}]_{1:p} & [\widetilde{\mathbf{r}}]_{2:p+1} & [\widetilde{\mathbf{r}}]_{3:p+2} & \ldots, & [\widetilde{\mathbf{r}}]_{N-p+1:N} \end{array}\right], \quad (14)$$

where $[\mathbf{a}]_{m:n}$ represents the vector composed of the mth to the nth elements of the vector $\mathbf{a}$. Consequently, $\mathbf{R}$ can be modeled as

$$\mathbf{R} = \mathbf{H}_p(f_o)\begin{bmatrix} \alpha\mathbf{h}_q^T(f_o) \\ \beta\mathbf{h}_q^T(2f_o) \\ \alpha^*\mathbf{h}_q^T(-f_o) \\ \beta^*\mathbf{h}_q^T(-2f_o) \end{bmatrix}. \quad (15)$$

The estimation of f_o is equivalent to the conventional spectral estimation. Several super-resolution techniques, such as MUSIC and ESPRIT [14], can be employed. As the ESPRIT algorithm yields an elegant closed-form solution, we employ it here. Note that the data model (15) has the shift-invariant property [14]. We obtain $\mathbf{R}_1 = [\mathbf{I}_{p-1} \quad \mathbf{0}_{p-1}]\mathbf{R}$ and $\mathbf{R}_2 = [\mathbf{0}_{p-1} \quad \mathbf{I}_{p-1}]\mathbf{R}$. It has been proved that the eigenvalues of $\mathbf{\Phi} = \mathbf{R}_1^\dagger\mathbf{R}_2$ are given by $e^{j2\pi f_oT_s}, e^{j2\pi 2f_oT_s}, e^{-j2\pi f_oT_s}$

and $e^{-j2\pi 2 f_o T_s}$. Let us define the four eigenvalues of $\mathbf{\Phi}$ as $\lambda_1, \ldots, \lambda_4$. Since $1/T_s > 4f_o$, the estimate of f_o is given by

$$\hat{f}_o = \frac{1}{2\pi T_s} \arg(\lambda_2\lambda_3 + (\lambda_1\lambda_4)^*). \tag{16}$$

Once we achieve the estimate of f_o, it can be used in (8) to further extract the phase information.

IV. Simulation Results

The performance of the proposed ARIPS is evaluated by simulations. We consider two cases with and without accurate knowledge of f_o, respectively. In order to avoid the integer ambiguity issue, we assume 100m $< d_i <$ 1km and follow the discussion in Section III-A to design f_c, f_d and f_o. For example, f_c = 10 MHz, f_d = 150 KHz, and f_o = 120 Hz. The modeling error $-(f_o/2)\eta_{12}$ is smaller than 0.0004, which corresponds to a TDOA estimation error of 2.67 ns. It indicates the TDOA estimate will have an error floor no less than a few nanoseconds. Moreover, τ_1 and τ_2 (or ϕ_1 and ϕ_2) are randomly generated in each Monte Carlo run following a uniform distribution in the range of $[100, 1000]/3 \times 10^8$ (or $[0, 1]$). The signal length is 100 millisecond (ms). Assuming $a_1 = b_1$, $a_2 = b_2$ and $a_1^2 d_1^2 = a_2^2 d_2^2$ according to the path loss model, we define the signal-to-noise ratio (SNR) as $(a_1^2 + a_2^2)/2\sigma^2$. This is equivalent to transmitting the dual-tone signals with the same amplitudes at two nodes, and the attenuated AWGN channels weaken the signals according to the path loss model.

Fig. 2 (or Fig. 3) shows the root mean square error (RMSE) of the estimated TDOA (or $\hat{f}_o$) vs. SNR, where the RMSE is defined as $\sqrt{1/N_{\rm exp} \sum_{n=1}^{N_{\rm exp}} \|\hat{\tau}_{12}(n) - \tau_{12}(n)\|^2}$, with $N_{exp} = 100$ the number of Monte Carlo runs, and $\hat{\tau}_{12}(n)$ and $\tau_{12}(n)$ the estimate and the true value of τ_{12} at the nth run, respectively. The performance of the TDOA estimate with the accurate f_o (the solid line) is about 3 dB better than the one with the estimated f_o (the solid line with circle markers) at high and moderate SNR. Both of them can achieve a few nanoseconds accuracy corresponding to distance errors of tens of centimeters at high SNR. The performance difference between the TDOA estimator with accurate f_o and the one without increases as the SNR decreases, but it increases slowly when the RMSE of $\hat{f}_o$ is smaller than 1 Hz. Furthermore, as shown in Fig. 3, the RMSE of $\hat{f}_o$ is smaller than 1 Hz when SNR > -2.5 dB, and can reach a few 10^{-3} Hz at high SNR. The proposed ARIPS is not so sensitive to the estimation error of $\hat{f}_o$ according to Fig. 2 and Fig. 3.

Fig. 4 denotes the localization performance of the ARIPS with SNR = 20 dB, where the SNR is defined as before. The "□" markers indicate five anchors, which are at the corners of a 100 m × 100 m square and the origin of the square, respectively. The "○" markers illustrate the true positions of the targets, which are randomly generated. We employ the LS estimator discussed in [10] to estimate target positions, and use the anchor at the origin as the reference node. The estimated positions with the accurate f_o and the estimated f_o ($\hat{f}_o$) are denoted by the "+" and "×" markers, respectively. Both of

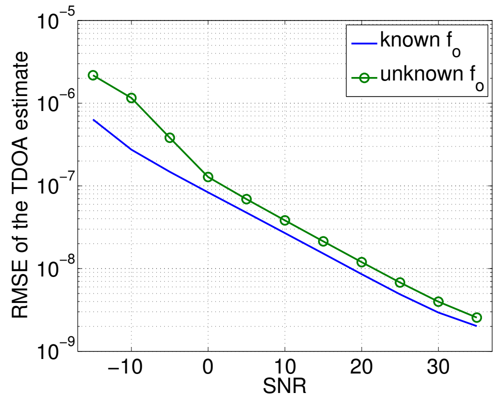

Fig. 2. The RMSE of the TDOA estimate vs. SNR

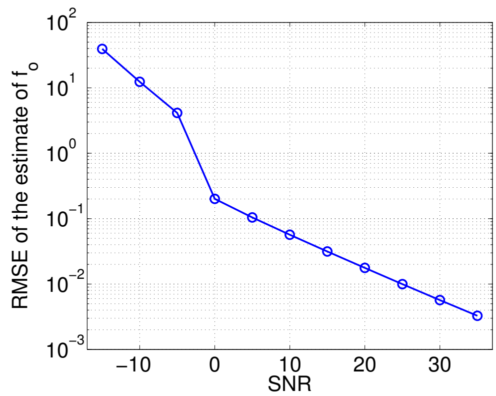

Fig. 3. The RMSE of $\hat{f}_o$ vs. SNR

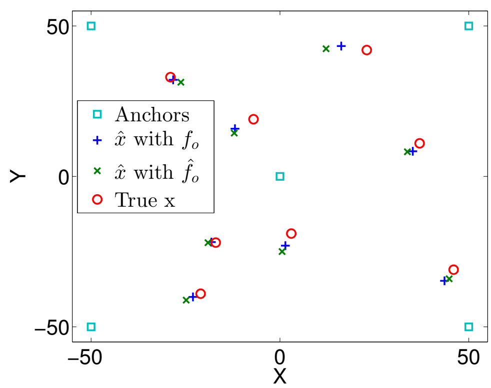

Fig. 4. Examples of the localization performance of the ARIPS, SNR = 20dB

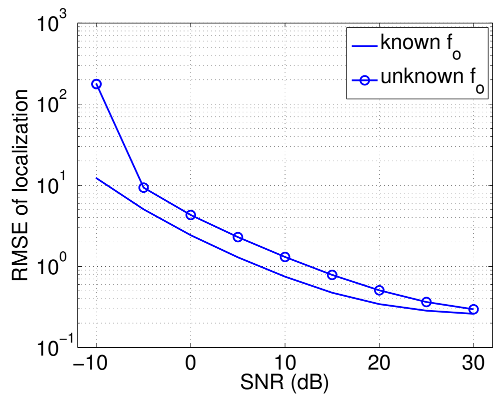

Fig. 5. The RMSE of the localization performance of the ARIPS vs. SNR

them obtain good estimates. The estimator using the accurate f_o achieves slightly better performance than the one using the estimated f_o. We also evaluate the RMSE of the localization performance of the ARIPS vs. SNR in Fig. 5. The localization performance degradation with estimated f_o (the solid line with circle markers) is increasing compared to the one with accurate f_o (the solid line) as the SNR decreases. This is consistent with the results of the TDOA estimates.

V. Conclusions

We develop an asynchronous radio interferometric positioning system (ARIPS) using dual-tone signals. The ARIPS is robust to the CFO and random phases due to asynchronous oscillators. In ARIPS, two dual-tone signals with slightly different frequencies are transmitted by two nodes. The receiver node creates two low-frequency differential signals using a square-law device and an LPF. The phase difference of these two differential signals is extracted. It is approximately in a linear relation with the TDOA. Furthermore, we consider the case that we do not have the accurate knowledge of the frequency of the differential signal. We employ the ESPRIT algorithm to estimate the frequency, and then use the estimated frequency to extract the TDOA information. The obtained TDOAs can be used immediately in conventional TDOA-based localization algorithms. Simulation results confirm the efficiency of the proposed ARIPS. It can achieve centimeter ranging accuracy.

References

[1] N. Patwari, J. N. Ash, S. Kyperountas, A. O. III Hero, R. L. Moses, and N. S. Correal, "Locating the nodes: cooperative localization in wireless sensor networks," *IEEE Signal Process. Mag.*, vol. 22, no. 4, pp. 54–69, Jul. 2005.

[2] G. Mao, B. Fidan, and B. Anderson, "Wireless sensor network localization techniques," *Computer Networks*, vol. 51, no. 10, pp. 2529 – 2553, 2007.

[3] IEEE Working Group 802.15.4, "Part 15.4: Wireless Medium Access Control (MAC) and Physical Layer (PHY) Specifications for Low-Rate Wireless Personal Area Networks (LR-WPANs)," Dec. 2006.

[4] S. Gezici, Z. Tian, G. B. Giannakis, H. Kobayashi, A. F. Molisch, H. V. Poor, and Z. Sahinoglu, "Localization via ultra-wideband radios: a look at positioning aspects for future sensor networks," *IEEE Signal Process. Mag.*, vol. 22, pp. 70–84, Jul. 2005.

[5] M. Maróti, B. Kusy, G. Balogh, P. Völgyesi, A. Nádas, K. Molnár, S. Dóra, and Á. Lédeczi, "Radio interferometric geolocation," in *ACM SenSys*, San Diego, California, USA, 2005, pp. 1–12.

[6] B. Kusy, J. Sallai, G. Balogh, A. Ledeczi, V. Protopopescu, J. Tolliver, F. DeNap, and M. Parang, "Radio interferometric tracking of mobile wireless nodes," in *ACM MobiSys*, San Juan, Puerto Rico, 2007, pp. 139–151.

[7] B. Kusy, A. Ledeczi, and X. Koutsoukos, "Tracking mobile nodes using RF Doppler shifts," in *ACM SenSy*, Sydney, Australia, 2007, pp. 29–42.

[8] H. Chang, J. Tian, T. Lai, H. Chu, and P. Huang, "Spinning beacons for precise indoor localization," in *ACM SenSys*, Raleigh, NC, USA, 2008, pp. 127–140.

[9] D. Zhang, Y. Liu, X. Guo, M. Gao, and L. M. Ni, "On distinguishing the multiple radio paths in RSS-based ranging," in *IEEE INFOCOM*, Orlando, FL, USA, Mar. 2012, pp. 2201 –2209.

[10] P. Stoica and J. Li, "Lecture notes - source localization from range-difference measurements," *IEEE Signal Process. Mag.*, vol. 23, no. 6, pp. 63–66, Nov. 2006.

[11] Y. Wang and G. Leus, "Reference-free time-based localization for an asynchronous target," *EURASIP J. Advances in Signal Processing*, Sept. 2011, accepted.

[12] C. Wang, Q. Yin, and Q. Wang, "An efficient ranging method for wireless sensor networks," in *IEEE ICASSP*, Dallas, TX, USA, Mar. 2010, pp. 2846 –2849.

[13] X. Li and K. Pahlavan, "Super-resolution TOA estimation with diversity for indoor geolocation," *IEEE Trans. Wireless Commun.*, vol. 3, no. 1, pp. 224 – 234, Jan. 2004.

[14] R. Roy and T. Kailath, "ESPRIT-estimation of signal parameters via rotational invariance techniques," *IEEE Transactions on Acoustics, Speech and Signal Processing*, vol. 37, no. 7, pp. 984 –995, Jul. 1989.