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A Robust Range Accuracy Adaptation Criterion Based on ZZLB for CPS

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Abstract

Cognitive radio (CR) provides a theoretical foundation to achieve the cognitive function and collaborative function for the positioning nodes. Under this trend, the cognitive positioning system (CPS) has emerged. But the limitation of the traditional range accuracy adaptation criterion based on Cramér-Rao Lower Bound (CRLB) makes it very diffcult to put CPS into practices.To overcome this problem, it is necessary to further study the criterion in complex noise environment. Based on the time of arrival (TOA) location estimation algorithm, we analyze the performance of the range accuracy adaptation algorithm, which take the Ziv-Zakai lower bound information as the CPS parameter optimization criterion. Simulation results show that the bound can providemore complete range accuracy adaptation information compared with CRLB. Furthermore, we can improve the positioning accuracy by means of enhancing the system signal-to-noise ratio (SNR), adjusting the system bandwidth and increasing the observation duration.

***Keywords**: cognitive radio, cognitive positioning system, range accuracy adaptation, Ziv-Zakai lower bound*

1. Introduction

With the rapid development of mobile communication technology, various applications based on mobile terminal are booming. Over the past few decades, the demand for Location Based Services (LBS) has grown explosively. The LBS have become one of basic service in the current information society. So far, there are multiple types of wireless positioning technology. However, each technology has different limits on network standard or signal mode, which restrict its positioning range and positioning accuracy. Therefore, the positioning system with accuracy adaptation function is attracting more and more researchers' attention. The emergence of CR technologyprovides a new perspective for in-depth analysis of CPS.Compare to the traditional radio, the CR introduces two main different features, cognitive capability and reconfigurability. And CR allows same frequency bands tobe used simulaneously by primary user and secondary user [1]. In [2] the CPS-based indoor and outdoor positioning system was presented by Celebi, which can adaptively adjust system parameters according to the variation of the surrounding environment. Theoretically, it can be applied to all kinds of complicated conditions. That is to say, we would easily locate each other with the level of meters or even centimeters, even in complex indoor environment or in caves and other regions where GPS can't normally coverage. In practice, the CPS can realize the objective of positioning by utilizing multiple measurement parameters, such as ToA/TDoA, DoAor RSSI [3]. But TOA-based range estimation technology can achieve high positioning accuracy under different environments, so most of researchers on CPS tend to select it as the positioning technology.

At present, the range accuracy adaptation research based on CPS is still on the initial stage [4]. It is necessary to further study the estimation error lower bound if we want to put range accuracy adaptation into practices [5]. The bound plays a fundamental role for evaluating the performance of a specific TOA-based estimator. In previous studies, the CRLB information in transmitter side generally was utilized as the parameter optimization criterion for range accuracy adaptation theory. In [6], Celebiet al. proposed a CR positioning system with accuracy adaptation function, and put forward a CRLB-based range accuracy adaptation algorithm, which can be realized by dynamically controlling positioning parameters in CPS. Compared with those conventional positioning systems, the CPS positioning nodes have both cognitive feature and

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collaborative feature [7, 8], and which makes it possible to easily realize range accuracy adaptation. Celebiet al. mainly analyzed the factors that affect the positioning precision, such as disperse spectrum and SNR.

But the previous analysis only limits on Additive White Gaussian Noise (AWGN) channel environments. Meanwhile, the CRLB can provide an accurate theoretical lower bound only under the condition of high SNRs or long observation duration [9-11], which leads to a problem that the CRLB-based range accuracy adaptation model cannot give the complete adaptive information in entire SNR domain or in more complex noise environments. Obviously, it is unable to meet the demand of future CPS application. So it's particularly important to study the range accuracy adaptation problem in more complex noisy environments. However, the question is how to choose a precision lower bound as the parameter optimization criterion in such circumstance? If we continue to consider CRLB as the criterion, its inherent defects cannot be avoided. While Ziv-Zakai lower bound (ZZLB) can provide a tighter lower limit than CRLB, furthermore, it can give different thresholds in different SNR domain. So it can characterize the mean squared estimation error better. In [12], Dardari has studied TOA estimation-based error lower bound problem in broadband system or UWB system under complex multipath environment. Its research results show that ZZLB is more effective in low SNR region than CRLB. And in [13], Amigo et al. also proved its asymptotically unbiased feature. Hence, considering that the advantage of ZZLB, this paper attempt to utilize the accuracy lower bound information provided by ZZLB as the CPS parameter optimization criterion under complex additive noise environment. The research is the further expand of the CPS range accuracy adaptation theory in AWGN environments.

The remainder of the paper is organized as follows. The system model is described in section 2. Section 3 reviews the deduction of the ZZLB. In section 4, we analyze the probability of error and derive associated ZZLB for the wide-band system. Simulation results are presented and discussed in section 5. Finally, section 6 concludes the paper.

2. The System Model

As described in [6], Figure 1 gives the CPS architecture. In the architecture, CPS is mainly composed of four awareness engines and one adaptive waveform generator/processor. And spectrum awareness engine is responsible for most of tasks related to dynamic spectrum. Similarly, the main responsibility of environment awareness engine is to capture information such as channel attenuation and time delay. In addition, location awareness engine mainly handle tasks related to positioning information.

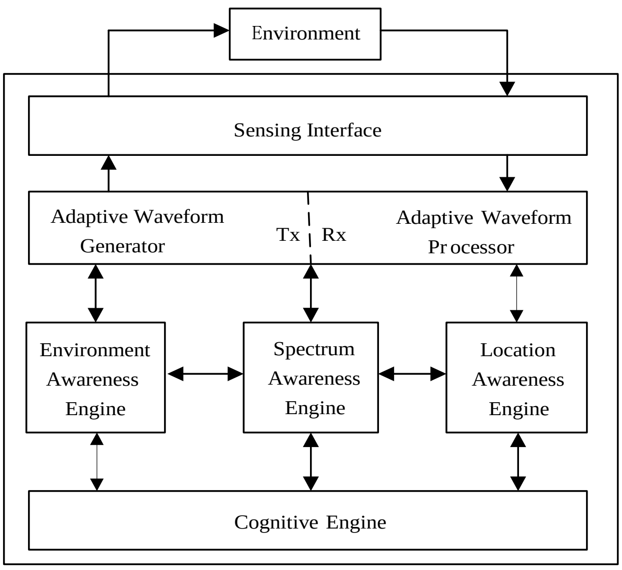

Figure 1. Simplified block diagram for CPS

Most importantly, cognitive engine supervise all the other engines to effectively realize the goal driven and adaptively process the related tasks, then the engine autonomously selects the optimal system parameters by using the information collected from other engines.

Based on the above architecture, we consider utilizing the Second-Derivative Gaussian pulse as the baseband signal $s(t)$, and through a single-path additive noise communication channel, the received signal can be expressed as:

$$r(t) = \xi s(t-\tau) + n(t) \tag{1}$$

Where ξ and τ correspond to the channel attenuation factor and the time delay, respectively. We assume that the parameter ξ is known. The TOA τ is the only parameter that need be estimated, which uniformly distributes in interval $[0, T_a]$. $n(t)$ denote the additive independent band-limited noise. And $s(t)$ is:

$$s(t) = \frac{1}{\sqrt{3T_s/8}}\left[1-4\pi\left(\frac{t}{T_s}\right)^2\right]\exp\left[-2\pi\left(\frac{t}{T_s}\right)^2\right] \tag{1}$$

Where T_s is a variable that affect the width of the transmitted pulse.Now our goal is to obtain the estimation $\hat{\tau}$ of τ by observing the received signal $r(t)$ in interval $[0, T_{ob}]$, where $T_{ob} > T_a + T_s$.

3. The Ziv-Zakai Lower Bound

The research on the lower bound of accuracy provides more complete range accuracy adaptive information for CPS. In this section we present a short review of the ZZLB based on [14]. The expression of the bound is computed by subtly converting the related issue into a binary detection problem. And in the paper we utilize binary detection to process the TOA estimation τ between the primary user and the secondary user. Now consider the following binary hypothesis tests.

$$\begin{aligned} &\mathrm{H}_0 : \tau = a; && r(t) = s(t-\tau) + n(t)\big|\tau = a \\ &\mathrm{H}_1 : \tau = a+h; && r(t) = s(t-\tau) + n(t)\big|\tau = a+h \end{aligned} \tag{2}$$

We assume that $h > 0$ and $a, a+h \in [0, T_a]$. Consider now the following suboptimal detection criteria.

$$\left|\hat{\tau} - a\right| \underset{\mathrm{H}_0}{\overset{\mathrm{H}_1}{\gtrless}} \left|\hat{\tau} - a - h\right| \tag{3}$$

That is if $\left|\hat{\tau} - a\right| < \left|\hat{\tau} - a - h\right|$, we decide on a. Otherwise, we decide on $a+h$.Hence, the minimum error probability is given by:

$$\frac{1}{2} p\left\{\hat{\tau} - a > h/2 \mid a\right\} + \frac{1}{2} p\left\{\hat{\tau} - a - h \le -h/2 \mid a+h\right\} \tag{4}$$

The first term of (5) means the probability with deciding on H_1 when H_0 is true. And the second term means the probability with deciding on H_0 when H_1 is true. Let $p_e(a, a+h)$ denote the minimum attainable probability of error for deciding between H_0 and H_1. Therefore:

$$p_e\left(a,a+h\right)\le\frac{1}{2}p\left\{\varepsilon>h/2\mid a\right\}+\frac{1}{2}p\left\{\varepsilon\le -h/2\mid a+h\right\} \tag{5}$$

Where ε is the estimation error, and $\varepsilon=\hat{\tau}-\tau$. By integrating (6) over the interval $\left[0,T_a-h\right]$, we have:

$$\begin{aligned}\int_0^{T_a-h} p_e(a,a+h)da &\le \int_0^{T_a-h}[\frac{1}{2}p\left\{\varepsilon>h/2\mid a\right\}+\frac{1}{2}p\left\{\varepsilon\le -h/2\mid a+h\right\}]da\\ &=\frac{1}{2}\int_0^{h}p\left\{\varepsilon>h/2\mid a\right\}da+\frac{1}{2}\int_h^{T_a-h}p\left\{\mid\varepsilon\mid\ge h/2\mid a\right\}da\\ &+\frac{1}{2}\int_{T_a-h}^{T_a}p\left\{\varepsilon<-h/2\mid a\right\}da\\ &\le\frac{1}{2}\int_0^{T_a}p\left\{\mid\varepsilon\mid\ge h/2\mid a\right\}da\end{aligned} \tag{6}$$

For convenience, we define the following function:

$$F\left(x\right)\triangleq\frac{1}{T_a}\int_0^{T_a}p\left\{\left|\varepsilon\right|\ge x\mid a\right\}da \tag{7}$$

Where a obeys uniformly distribution over $\left[0,T_a\right]$. And $F\left(x\right)$ denotes the average of $p\left\{\left|\varepsilon\right|\ge x\mid a\right\}$. Then from (7) we have:

$$\int_0^{T_a-h} p_e(a,a+h)da\le\frac{T_a}{2}F\left(h/2\right) \tag{8}$$

From (9) we can see that it is meaningful only when $h\le T_a$. Because the integral value is negative if $h>T_a$, in this case zero is the best lower bound. Multiplying both sides of (9) by $2h/T_a$ and integrating it over $\left[0,T_a\right]$, we have:

$$\begin{aligned}\frac{2}{T}\int_0^{T_a}h\int_0^{T_a-h}p_e(a,a+h)\,\mathrm{d}\,a\,\mathrm{d}\,h &\le\int_0^{T_a}hF(h/2)dh\\ &=4\int_0^{T_a/2}xF(x)dx\\ &\le 4\int_0^{T_a}xF(x)dx\\ &=2x^2F(\mathrm{x})\mid_0^{T_a+}-2\int_0^{T_a+}x^2dF(\mathrm{x})\end{aligned} \tag{9}$$

It is obvious that $F\left(T_a^{+}\right)=0$. Let us define $\overline{\varepsilon^2}=-\int_0^{T_a}x^2dF\left(x\right)$ and substitute it into (10), we have:

$$\overline{\varepsilon^2}\ge\frac{1}{T_a}\int_0^{T_a}h\int_0^{T_a-h}p_e(a,a+h)\,\mathrm{d}\,a\,\mathrm{d}\,h \tag{10}$$

In particular, if $p_e\left(a,a+h\right)=p_e\left(h\right)$, that is, the minimum error probability is independent of a. We can simplify (11) and obtain:

$$\overline{\varepsilon^2}\ge\frac{1}{T_a}\int_0^{T_a}h\left(T_a-h\right)p_e\left(h\right)\mathrm{d}\,h \tag{11}$$

Inequality (12) is the expression of the basic lower bound named ZZLB. The bound provides a fundamental lower limit model for the positioning estimation error researches in different kinds of noise environments. Different with CRLB, ZZLB can give a tighter lower bound in any SNR region. That is to say, the ZZLB-based adaptive model can provide more perfect adaptive information for CPS, and it will be very helpful for us to study how the different SNR value influence the positioning accuracy.

4. Analysis of The ZZLB for Wide-Band System

In this section, we mainly concentrate on the deduction of the minimum error probability $p_e(h)$ in (12) under complex additive noise environments. To consider the binary detection problem presented by (3), we define the Log Likelihood Ratio Test (LLRT) between the hypothesis H_0 and H_1 as follows:

$$l(\mathrm{r}) = \ln \frac{p(\mathrm{r} \mid \mathrm{H}_1)}{p(\mathrm{r} \mid \mathrm{H}_0)} \tag{12}$$

Where $p(\mathrm{r} \mid \mathrm{H}_i)$ is the conditional probability density of the received data vector r under hypothesis H_i. It is necessary noted that, we may obtain r by directly sampling from the received signal under AWGN environment since the sampling data of received signal is unrelated. However, under additive gaussian non-white noise environments, the same direct way cannot be utilized to obtain the conditional probability density due to the related feature between the sampling data. So in this situation, we firstly must figure out how to process the decorrelation or whitening to the received signal.

To obtain the conditional probability density of received signal matrix, we make use of Karhunen-Loéve expansion [15], a classical decorrelation way, to process the received signal in the interval $[0, T_{\mathrm{ob}}]$ using a suitable complete orthonormal basis $\{\Phi_m(t)\}_{m=1}^{M}$, which satisfies the condition:

$$\int_0^{T_{ob}} \Phi_j(\mathrm{t}_2)\,\mathrm{Rn}(\mathrm{t}_1 - \mathrm{t}_2)\,\mathrm{dt}_2 = \mathrm{K}_j \Phi_j(\mathrm{t}_1) \tag{13}$$

Where $\mathrm{Rn}(\mathrm{t}_1 - \mathrm{t}_2)$ is the kernel function of the integral equation. $\Phi_j(\mathrm{t})$ corresponds to the characteristic function of the integral equation. K_j denotes the eigenvalues, which also is the variance of corresponding expansion coefficients. Now we have:

$$r(t) = \sum_{m=1}^{M} r_m \Phi_m(t), \quad n(t) = \sum_{m=1}^{M} n_m \Phi_m(t) \tag{14}$$

Where the expansion coefficients can be expressed as follows:

$$r_m = \int_0^{T_{ob}} r(t)\Phi_m(t)\,dt \tag{15}$$

Clearly, through a series of related operations, the expansion coefficients $\{r_m\}$ are not the direct sampling values of the received signal $r(t)$. But these coefficients completely retain the whole characteristic of the original received signal, and the Gaussian random variable element of the data vector is independent. In other words, the data vector is equal to direct sampling samples of the reception. Now $r(t)$ and $n(t)$ could be denoted by

$\mathrm{r}=\left[r_1, r_2, \cdots, r_M\right]^T \in \mathrm{R}^M$ and $\mathrm{n}=\left[n_1, n_2, \cdots, n_M\right]^T \in \mathrm{R}^M$, respectively. In a similar way, we have the expansion coefficients $\mathrm{s}=\left[s_1, s_2, \cdots, s_N\right]^T \in \mathbb{R}^N$ of the sending signal $\mathrm{s(t)}$, where $M=\lfloor 2WT_{ob} \rfloor+1, N=\lfloor 2WT_s \rfloor+1$. Since $T_s < T_{ob}$, we can obtain $N < M$. Expression (1) can be written equivalently as:

$$\mathrm{r}=\mathrm{H}^{(\tau)}\mathrm{s}+\mathrm{n} \tag{16}$$

Where $\mathrm{H}^{(\tau)} \in \mathbb{R}^{M \times N}$ represent the transform matrix related to the TOA values. And the conditional probability density function of r is:

$$p\{\mathrm{r} \mid \mathrm{H}_i\}=\frac{1}{\det(\pi \mathrm{K}_i)} \cdot \exp\{-\mathrm{r}^* \mathrm{K}_i^{-1} \mathrm{r}\} \qquad i=0,1 \tag{17}$$

Where r^* means conjugate transpose matrix of r.

Assuming that the hypothesis H_0 and H_1 are equally likely to occur (i.e., $p(\mathrm{H}_0)=p(\mathrm{H}_1)=1/2$). Then we can draw that the threshold of LLRT is zero according to estimation theory. That is to say, we decide on H_1 if $l(\mathrm{r}) \geq 0$, otherwise, we decide on H_0. Hence, we have:

$$p_e(h)=\frac{1}{2}\int_0^{\infty} p(l(\mathrm{r}) \mid \mathrm{H}_0)dl+\frac{1}{2}\int_{-\infty}^{0} p(l(\mathrm{r}) \mid \mathrm{H}_1)dl \tag{18}$$

Now substituting (18) into (19), we have:

$$p_e(h) \approx \exp\left[a(h)+b(h)\right] erfc\left(\sqrt{2b(h)}\right) \tag{19}$$

The detailed arithmetic can be found in [16]. If we assume that transmitter and receiver are synchronous, the time difference of arrival (TDOA) information can be replaced by TOA information. So we have:

$$a(h)=-\frac{T_{ob}}{2\pi}\int_0^{\infty} \ln\left[1+\kappa(\omega,h)\right]d\omega \tag{20}$$

$$b(h)=\frac{T_{ob}}{2\pi}\int_0^{\infty} \frac{\kappa(\omega,h)}{1+\kappa(\omega,h)}d\omega \tag{21}$$

$$\kappa(\omega,h)=\frac{\left[S(\omega)/N(\omega)\right]^2}{1+2S(\omega)/N(\omega)} \cdot \sin^2(\omega h/2) \tag{22}$$

$$erfc(x)=\frac{1}{\sqrt{2\pi}}\int_x^{\infty} e^{-t^2/2}dt \tag{23}$$

Without loss of generality, there is an assumption that the studied signal power spectrum and the noise power spectrum are approximately flat in the target band. That is, $S(\omega)$

and $N(\omega)$ can be represented by S and N, respectively. Simplifying (23) and substituting it into (21) and (22) immediately yields:

$$a(h) = -\frac{T_{ob}}{2\pi}\int_W \ln\left[1 + SNR\cdot\sin^2(\omega h/2)\right]d\omega \tag{24}$$

$$b(h) = \frac{T_{ob}}{2\pi}\int_W \frac{SNR\cdot\sin^2(\omega h/2)}{1 + SNR\cdot\sin^2(\omega h/2)}d\omega \tag{25}$$

Where,

$$SNR \triangleq \frac{[S/N]^2}{1 + 2S/N} \tag{26}$$

Note that the SNR in (27) is no longer the conventional Signal to Noise Ratio. Now substituting (25) and (26) into (20) and (20) into (12) successively, ZZLB expression can be written as:

$$ZZLB = \begin{cases} \dfrac{T_a^2}{12} & (WT_{ob}/2\pi)SNR < \alpha \\ threshold & \alpha < (WT_{ob}/2\pi)SNR < \beta \\ \dfrac{12}{W^2}\cdot\dfrac{1}{(WT_{ob}/2\pi)SNR} & (WT_{ob}/2\pi)SNR > \beta \end{cases} \tag{27}$$

For the convenience of analysis, we may define $(WT_{ob}/2\pi)SNR$ as the post-integration SNR. In (28) there is an apparent transition region for ZZLB, which divides the entire SNR region into two unrelated parts. Essentially, the bound varies exponentially with the post-integration SNR in the threshold region. When $(WT_{ob}/2\pi)SNR < \alpha$, noise is dominant in the received signal. We can only draw the conclusion that the TOA estimation included in the interval $[0, T_a]$. When $(WT_{ob}/2\pi)SNR > \beta$, the estimation performance is closely characterized by the CRLB. Now we illustrate the result in Figure 3.

α and β are the lower and upper limits of the threshold region, respectively. And α corresponds to the point where the performance level of $T_a^2/12$ drop down 3dB. It is approximately equal to 0.92 or equal to -0.36dB. Similarly, β is defined as the point where the lower bound is 3dB above the performance level described by the third line of (28). The point determines the boundary between the small and large estimation errors, so it is an important factor to affect the composite bound presented by (28). And β is the approximate solution to the following equation:

$$(\beta/2)\,erfc\left(\sqrt{\beta/2}\right) = (6/WT_a)^2 \tag{28}$$

5. Simulations Results and Discussion

In this section we conduct related computer simulations. All results are discussed under the assumption that the involved baseband signal and the additive noise model have nearly flat power spectrum in target band. Obviously, the AWGN meet the above demand, and it is also valid for those common Gaussian non-white noises such as pink noise or red noise, etc.

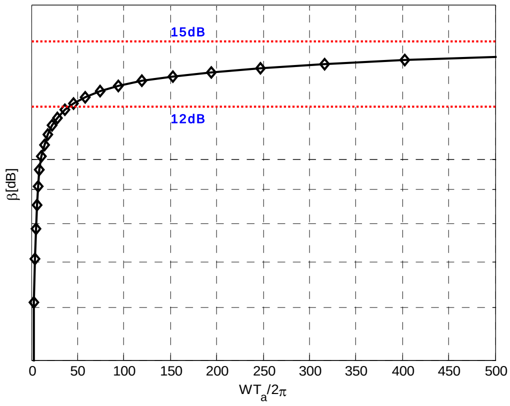

Figure 2. β versus $\mathrm{WT_a}/2\pi$

In fact, it is difficult for us to obtain the exact solution about β. For convenience to analysis, Figure 2 gives the value β as a function of $WT_a/2\pi$. From the figure we can see that when $WT_a/2\pi$ is greater than 50, the point β approximately varies from 12dB to 15dB.

In (28), there are some related parameters that affect the performance of the positioning accuracy such as the SNR, the system bandwidth and the observation duration. In what follows, we would analyze the effects of these parameters and give related computer simulations.

(1) In Figure 3, the simulation environments set as, (i) $-7dB \le (WT_{ob}/2\pi)SNR \le 30dB$. (ii) The system bandwidth is $W = 50MHZ$. (iii) The TOA prior distribution interval is $[0, 1\mu s]$.

For comparison, Figure 3 simultaneously shows the MSE curves predicted by CRLB and ZZLB. We can observe that there is a distinct segmentation phenomenon about ZZLB, which can provide a tighter and more realistic lower bound than CRLB in moderate and low SNR region. We next observe that ZZLB quickly approaches the performance predicted by CRLB in high SNR region. And the reason is that the received signal is completely dominated by noise in low SNR region and the estimate error depends only on the priori distribution domain. Furthermore, the point can affect the boundary of the threshold region. And the point can be adjusted by the system bandwidth.

Aimed at ZZLB, We have the conclusion that under the same condition, the estimate value only depends on the prior distribution of the TOA in low SNR region. And the MSE approximately equal to the values predicted by CRLB in high SNR region, which is an optimal estimation in this case. For the threshold area the TOA estimation error decreases exponentially with the SNR.

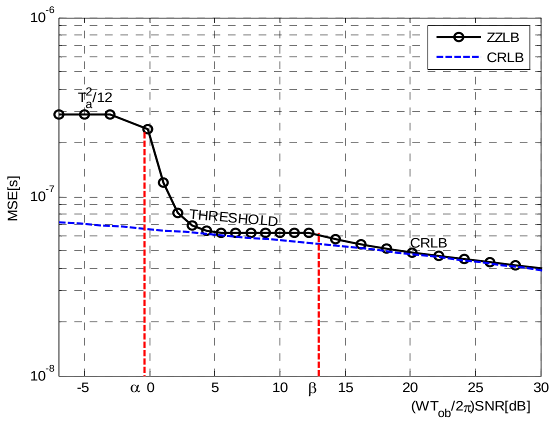

Figure 3. The Ziv-Zakai composite lower bound

(2) As we all know, since the available frequency bandwidth among the dynamic spectrum resources are random in CPS. As a result, the CR users can always flexibly utilize the dynamic spectrum resources detected by the system according to the given accuracy. To illustrate the relationship between the frequency bandwidth and estimation MSE in different SNR region, we set the simulation environments as, (i) the SNR are 5dB, 15dB, 25dB, 35dB, respectively. (ii) the observation duration is $T_{ob} = 2\mu s$. (iii) the interval of the frequency bandwidth is $30MHZ \sim 130MHZ$. The simulation result is illustrated in Figure 4.

From Figure 4 it appears that the positioning accuracy tends to improve with the increasing of the system bandwidth, especially for the high SNRs. However, in low SNR region the trend is not very obvious. Therefore, for the severe channel environments, we cannot simply rely on increasing the system bandwidth to improve the positioning accuracy. Actually, we should tend to improve the channel environment or enhance the transmitted signal power. Furthermore, we can improve the performance of positioning accuracy by increasing the system bandwidth. Nevertheless, excessive bandwidth will need higher requirements for the positioning system. How to achieve the optimal balance between the system complexity and the positioning accuracy still remains as an open question.

(3) Figure 5 shows the relationship between the observation duration and the positioning estimation MSE. The simulation environments set as, (i) the SNR are 5dB, 15dB, 25dB, 35dB, respectively. (ii) the system bandwidth is 30 MHZ. (iii) the interval of observation duration is $2\mu s \sim 4\mu s$.

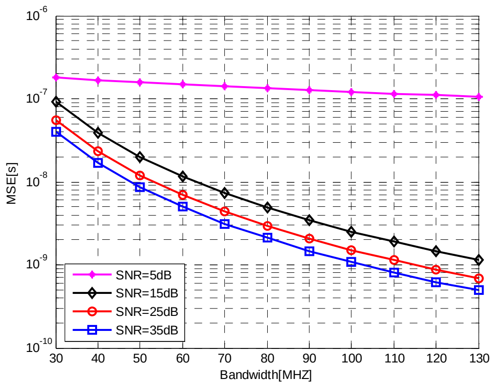

Figure 4. The bandwidth versus estimation MSE

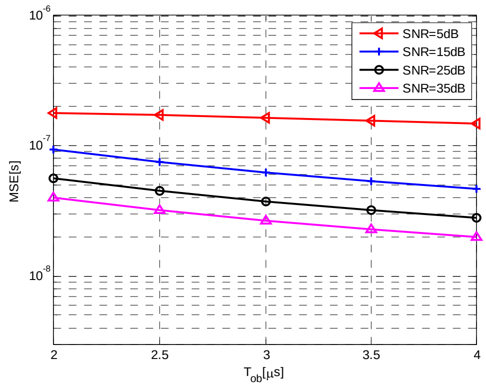

Figure 5. The observation duration versus estimation MSE

From Figure 5, it can be noticed that increasing the observation duration is beneficial to improving the positioning accuracy especially in high SNRs. However, the improvement introduced by increasing the observation duration is not as obvious as increasing the system bandwidth. Meanwhile, we can also see that the positioning accuracy tends to improve along with the improvement of the SNR. In fact, if we want to decrease the TOA-based estimation error from the level of 10^{-7} to 10^{-8} at the SNR level of 15 dB (i.e., increasing the positioning accuracy from the level of 30m to 3m). We need expand the observation duration by about 10 times, that is, extending the observation duration from the level of $2\mu s$ to $20\mu s$. More importantly, the actual positioning systems need continuously estimate and update the location information of a mobile terminal from a series of measurement values. And it is significant for the real-time requirements of the system. So it is unreasonable to blindly extend the observation duration.

Obviously, from Figure 4 and 5 we can draw the conclusion that it is difficult to achieve significant improvement of positioning accuracy only by increasing the system bandwidth or extending the observation duration in low SNR environment. In fact we should firstly focus on improving the system SNR, and then consider the influence of other factors. In summary, we should take these factors into comprehensive consideration according to the target positioning accuracy in practical application. Consequently, we can acquire a good balance between the positioning accuracy and system implementation complexity.

6. Conclusion

This paper utilizes the TOA estimation-based ZZLB information in transmitter side as the parameter optimization criterion for CPS, which can improve the shortcomings of taking the CRLB information as the criterion. Meanwhile, we extend the range accuracy adaptation research to the more complex additive noise environments. Furthermore, the main factors that affect the performance of the positioning accuracy are also analyzed. Finally, simulation results show that by adjusting the system bandwidth, the transmitted power level and the observation duration, the CPS can cognitively optimize the parameter configuration and achieve the desired positioning accuracy with the minimum cost. Even though taking ZZLB information as the parameter optimization criterion would increase the computation complexity, it would still play a key role in putting positioning accuracy adaptation into practices for CPS.

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