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Low Complexity Tri-level Sampling Receiver Design for UWB Time-of-Arrival Estimation

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***Abstract*—In this paper, the effect of finite-level quantization on UWB time-of-arrival (TOA) estimation is investigated. The scheme of optimized quantization threshold combined with the post-quantization processing is derived, which is shown to provide satisfactory gains in the system performance. The TOA estimation errors of several low-resolution sampling approaches are compared via Monte Carlo simulation, where the tri-level quantizer is of particular interest due to its simplicity and capability. We demonstrate that the tri-level sampling receiver, with use of the proposed scheme provides an outstanding performance in TOA estimation with an affordable cost and low complexity.**

***Index Terms*—TOA, UWB, tri-level sampling, quantization.**

I. Introduction

Ultra-wideband (UWB) signaling with use of the time-of-arrival (TOA)-based ranging technique is a good candidate enabling accurate localization in cluttered environments, whereas the satellite navigation signals are not reliable [1]. It is a combined detection and estimation problem. The solution to this problem has been widely studied and several methods were proposed, including the maximum likelihood (ML) approach [2] and the Bayesian estimation technique which jointly estimates the first path delay and channel amplitudes [3]. Even though these estimators are superior in terms of performance, they are impractical for implementation. The Nyquist sampling for UWB signal is often needed in these estimators, which requires GHz ADCs [4] and hence makes it infeasible with the low-cost and low-power requirements imposed by real applications.

A solution was provided by limiting the resolution of ADC to only a few bits and has been explored in several literatures in communication applications [5], [6], [7], [8]. However, little work has been done in terms of the theoretical feasibility of low-bit ADC in UWB TOA estimation. While communication and TOA estimation are performing detection, there are significant differences between them. The low-resolution sampling techniques in communication systems cannot be directly applied to the TOA estimation as a result of the lack of amplitude information of arriving signals [2], which is not necessary in 2-PAM communication signal detections [9].

In this paper, we propose a scheme in improving the finite-level receiver performance with a focus on the tri-level quantization. The threshold-crossing (TC)-based method is employed due to its simplicity in hardware implementation. We determine the first path signal in multipath environment by optimizing the TOA decision threshold. Simulation results are displayed, which demonstrate the effectiveness of proposed scheme. We show that the tri-level sampling receiver, with use of the proposed scheme of optimal quantization threshold and post-quantization processing, approaches the performance of a full-resolution receiver.

II. System Model and Receiver Architecture

The received UWB signal can be typically modeled as

$$r(t) = \sum_{i=0}^{N_s-1} d_i s(t - iT_s) + n(t) \tag{1}$$

where T_s is the symbol duration, N_s is the total number of symbols, d_i is the information bit, $n(t)$ is the AWGN with two-sided PSD of $\sigma^2 = N_0/2$, and $s(t)$ is the received pulse waveform of total ξ multipaths. Here $s(t)$ can be rewritten as $s(t) = \sum_{j=1}^{\xi} \alpha_j p(t - \tau_j)$, where α_j, τ_j are the amplitude and delay of the j^{th} path respectively, and $p(t)$ is the transmitted pulse.

We assume that the received signal is quantized through a uniform quantizer with a quantization step of Δ and total L levels. Let the quantization level be represented as $l_n, n = 1, \cdots, L$. Therefore, with uniform quantization spacing, the threshold is $\theta_n = (l_n + l_{n+1})/2$, where $\Delta = \theta_{n+1} - \theta_n$, $n = 1, \cdots, L-1$. The sampling period is T under Nyquist sampling, and every symbol duration is sampled by K points. As a result, denote the kth sample within the ith period by $r_{i,k}$, and we have

$$r_{i,k} = \begin{cases} l_1, & r(iT_s + kT) < \theta_1 \\ l_n, & \theta_{n-1} \le r(iT_s + kT) \le \theta_n \\ l_L, & r(iT_s + kT) > \theta_{L-1} \end{cases} \tag{2}$$

where $i = 0, \ldots, N_s - 1$, $k = 0, \ldots, K-1$. The sampling period T also determines the minimum achievable variance of $T^2/12$ for TOA estimation [10]. The TOA value (τ_{TOA}) is defined as the first arrived path delay (τ_1), with the time-slot index $k_{TOA} = \lfloor \tau_{TOA}/T \rfloor$. Typically, k_{TOA} is assumed uniformly distributed on $[0, 1, \cdots, K_T - 1]$ [1], where K_T is the largest accessible value of k_{TOA} with $K_T \le K$. We notice that the region of $(0 \sim k_{TOA} - 1)$ is the noise region containing noise only and the remaining $K_T - k_{TOA}$ cells is the signal region containing the multipath signals.

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Since the received signal $r(t)$ is Gaussian, the probability mass function (pmf) of the quantizer output $r_{i,k}$ for each level is given by

$$P(r_{i,k} = l_n; s_{i,k}, \sigma) = \begin{cases} 1 - Q(\frac{\theta_n - s_{i,k}}{\sigma}), & n = 1 \\ Q(\frac{\theta_{n-1} - s_{i,k}}{\sigma}) - Q(\frac{\theta_n - s_{i,k}}{\sigma}), & n = 2, \cdots, L-1 \\ Q(\frac{\theta_{n-1} - s_{i,k}}{\sigma}), & n = L \end{cases} \quad (3)$$

where l_n is the quantization level, $Q(x)$ is the Gaussian Q function, $s_{i,k}$ is the received signal, and $s_{i,k} = 0$ represents the noise region. For simplicity, we define $p_n := P(r_{i,k} = l_n; s_{i,k}, \sigma)$, $q_n := P(r_{i,k} = l_n; 0, \sigma)$, where $k = 0, \ldots, K-1$.

III. Performance-Improving Techniques and Tri-Level Quantizer

A. *Optimized Quantization Threshold*

When UWB signal is input to the quantizer, lower quantization step causes the signal clipped, while higher step achieves a poor effective resolution. Thus, to avoid the errors caused by improperly chosen of the quantization step (Δ), the mechanism of an optimal choice of Δ should be used. To assess the performance when the analog input $s(t)$ is replaced by its quantization representation as (3), we can choose CRLB as the index for assessing the goodness of the quantization step setting. The lower bound of CRLB indicates that the quantized sample $s_{i,k}$ is approaching to analog input $s(t)$ with less error introduced, i.e., a good setting of quantization step. For simplicity, we use Fisher information J (the reciprocal of CRLB) to assess the quantization threshold setting, then adjust the threshold to maximize J of the signal sample $s_{i,k}$ as

$$J = \sum_{l_n} \frac{(\frac{\partial}{\partial s_{i,k}} P(r_{i,k} = l_n; s_{i,k}, \sigma))^2}{P(r_{i,k} = l_n; s_{i,k}, \sigma)} \quad (4)$$

Using (3), the maximum value of J can be calculated with parameter Δ, $s_{i,k}$ and σ available as $J(\Delta, s_{i,k}, \sigma)$, then the optimal quantization step corresponding to the maximum Fisher information is

$$\Delta_{opt} = \arg\max_{\Delta}(J(\Delta, s_{i,k}, \sigma)) := f_{\Delta}(s_{i,k}, \sigma) \quad (5)$$

where $s_{i,k}$ and σ are the parameters needed. With Δ_{opt} available, each quantization threshold θ_n can be obtained as

$$\theta_n = (n - L/2)\Delta_{opt} \quad n = 1, \cdots, L-1 \quad (6)$$

where L is the total number of quantization levels. For a b-bit ADC, $L = 2^b$, the minimum value is $L = 2$, which is a mono-bit($b = 1$) receiver. However, we are not restricted to these even level quantizers, we allow odd-levels, e.g. tri-level ($L = 3$) receiver.

The behavior of the Fisher information characteristics provides possibilities for maximizing the sampling performance through threshold adjustment. However, the statistical parameters $s_{i,k}$ and σ in (5) should be estimated before optimal threshold setting. To obviate the difficulty in jointly estimating $s_{i,k}$ and σ, we intend to obtain estimated signal mean value $\hat{s} := \mathbb{E}(s_{i,k})$ and σ in signal ($\Re^n$) and noise ($\Re^n$) region, respectively; where $\mathbb{E}(\cdot)$ is the mean function. Select one of the quantization threshold θ_C ($L/2 < C \leq L$), and the samples that crossing the threshold is $N_k^{l_n}$, where $n = C \sim L$. The chosen of C is to avoid the condition that $\sum_{n=C}^{L} N_k^{l_n}/N_t \approx 0$. From (3), we have $Q((\theta_{C-1} - s_{i,k})/\sigma) \approx \sum_{n=C}^{L} N_k^{l_n}/N_t$. Thereafter, $\hat{\sigma}$ of the analog input can be estimated in noise region by

$$\hat{\sigma} = \mathbb{E}_{k \in \Re^n} \left(\theta_{C-1} / Q^{-1} \left(\sum_{n=C}^{L} N_k^{l_n}/N_t \right) \right) \quad (7)$$

In signal region ($\Re^s$), the estimated mean value $\hat{s}$ can be written as

$$\hat{s} = \mathbb{E}_{k \in \Re^s} \left(\theta_{C-1} - \hat{\sigma} \cdot Q^{-1}(\sum_{n=C}^{L} N_k^{l_n}/N_t) \right) \quad (8)$$

where $\hat{s}$ can replace $s_{i,k}$ in (5) to avoid the need of calculating the signal in each sampling cells. The quantization threshold is only need to be updated after N_t training pulses, which reduces the complexity of the threshold setting.

In order to estimate the signal region ($\Re^s$) and obtain $\hat{s}$, we choose to perform sliding window clustering for all the samples with length of (D) and step of $D/2$. Then, we can obtain cluster as G_n, n is the cluster index, with $[0 \sim N_b]$, where $N_b = \lfloor 2K_T/D \rfloor$. In each cluster, we can calculate $EG_n = \mathbb{E}_{k \in D}(\sum_{n=C}^{L} N_k^{l_n})$, which is related to signal strength. Select the cluster with maximum value of EG_n as the estimated signal region. Then, other clusters is the estimated noise region and can be used to calculate $\hat{\sigma}$ by (7). With $\hat{\sigma}$ available, $\hat{s}$ can be obtained by (8), and the optimal quantization threshold of finite-level ADC can be adjusted by using (5) and (6).

B. *Suboptimal Weighting and TOA Decision Threshold*

After optimizing the quantization threshold, the performance of finite-level sampling receiver can be further improved by using post-quantization processing schemes. The TC based TOA method has the advantage of simple implementation and particularly attractive for finite-level quantization. However, conventional TC based methods [1], i.e., Normalized Threshold [11], Jump Back and Search Forward (JBSF), Serial Backward Search (SBS) [2], and set the threshold based on the noise level [1], do not achieve satisfactory performance for quantized samples. These methods do not consider the SNR condition, and the selection of threshold by Monte Carlo simulation is computational and inelegant. In the following, a suboptimal weighting approaches is derived for obtaining the decision vector from quantized samples, and an optimized TOA threshold method is proposed by minimizing the error detection probability.

1) Suboptimal Weighting: Assume that θ_n are given, we can use N_t training cycles to estimate $p_n := \hat{P}(r_{i,k} = l_n; s_{i,k}, \sigma) \approx N_k^{l_n}/N_t$, $N_k^{l_n}$ is the number of samples that falling into quantization level l_n. Then the set

$N_k^{l_1}, \cdots, N_k^{l_L}$ obeys a multinomial distribution [12] with parameters $(p_1, \cdots, p_L)$ in signal region, and $(q_1, \cdots, q_L)$ in noise region. With the multinomial distribution function of $P(p_1, \cdots, p_L) = N_t! \Pi_{n=1}^{L} (p_n)^{N_k^{l_n}} / N_k^{l_n}!$ and $P(q_1, \cdots, q_L) = N_t! \Pi_{n=1}^{L} (q_n)^{N_k^{l_n}} / N_k^{l_n}!$ in signal and noise region, respectively. Upon observing a multinomial vector $N_k^{l_1}, \cdots, N_k^{l_L}$, it is convenient to express the maximum likelihood (ML) test in terms of the log-likelihood ratio (LLR) for optimal performance. The LLR is the ratio of the maximum probability of a result under two different hypotheses, i.e., signal present or not, as

$$\begin{aligned} T_k^{opt} &= \log \frac{P(p_1, \cdots, p_L)}{P(q_1, \cdots, q_L)} \\ &= \log \frac{N_t! \Pi_{n=1}^{L} (p_n)^{N_k^{l_n}} / N_k^{l_n}!}{N_t! \Pi_{n=1}^{L} (q_n)^{N_k^{l_n}} / N_k^{l_n}!} = \sum_{n=1}^{L} N_k^{l_n} \log(\frac{p_n}{q_n}) \end{aligned} \tag{9}$$

where $\log(\frac{p_n}{q_n}) := w_k^{opt}$. We remark that w_k^{opt} is the optimal weighting coefficients that are used to combine the quantized samples of $N_k^{l_n}$ under the criterion of LLR. The LLR depends on the quantization threshold, noise variance, the sampling rate and the probability that signal and noise in each quantization levels.

Very often that the optimal weighting coefficients w_k^{opt} are not available, since p_n is related to signal. Direct using the LLR of (9) is infeasible and too complicated, which involves the calculation of $\log()$. Thus, some practical and suboptimal methods are more preferred than the idealistic optimal one. When SNR is small, $p_n/q_n \approx 1$, we can perform a Taylors expansion of $\log(\frac{p_n}{q_n}) \approx p_n/q_n - 1$. The simplification obviates the calculation of $\log()$, and would not introduce significant differences, especially in low SNR regions. Based on the observing of $N_k^{l_n}$ for each quantization level, using $N_k^{l_n}/N_t$ to represent the unknown parameter $P_n \approx N_k^{l_n}/N_t$ is asymptotically optimal. So that, the practical version of decision vector (9) can be shown as

$$T_k = \sum_{n=1}^{L} N_k^{l_n} \log\left(\frac{N_k^{l_n}/N_t}{q_n}\right) \approx \sum_{n=1}^{L} N_k^{l_n} \left(\frac{N_k^{l_n}/N_t}{q_n} - 1\right) \tag{10}$$

where q_n can be calculated by (3) with $s_{i,k} = 0$ and known quantization threshold θ_n. With the decision vector available, the TOA path can be determined by using preset threshold [1].

2) Optimized TOA Decision Threshold: Before TOA decision, the preset threshold must be obtained. To derive the optimized decision threshold, minimizing the two kind TOA estimation errors (early detection and late detection [1]) can provide a feasible way.

Assume the probability that the decision vector T_k crossing the threshold in noise region ($\Re^n$) and signal region ($\Re^s$) is $p(\eta, \sigma_T), p(\eta, s_T, \sigma_T)$, where η is the TOA decision threshold, s_T and σ_T are the first and second moment of T_k, which is different from the statistical parameter $s_{i,k}$ and σ of the analog input in (5). It is shown in [12] that (9) has approximately a chi-square distribution (χ^2) with $\nu = (L-1)$ degrees of freedom in large samples. So, we have $p(\eta, \sigma_T) = Q_{\chi^2(\nu)}(\eta/\sigma_T^2)$, $p(\eta, s_T, \sigma_T) = Q_{\chi^2(\nu)}\left((\eta - s_T)/\sigma_T^2\right)$.

The error probability of early detection [10] is $P_{ed}|_{k_{TOA}} = 1 - (1 - p(\eta, \sigma_T))^{k_{TOA}}$, which means the estimator selects the incorrect sample prior to signal region. The late detection probability that the true TOA path is missed can be shown as $P_{ld}|_{k_{TOA}} = (1 - p(\eta, \sigma_T))^{k_{TOA}}(1 - p(\eta, s_T, \sigma_T))$, the first term $(1 - p(\eta, \sigma_T))^{k_{TOA}}$ means no sample crossing the threshold in noise region, the second term $(1 - p(\eta, s_T, \sigma_T))$ indicates that the true TOA path is missed. Assume that the TOA estimation error associated with early and late detection probability is $\rho_{ed}|_{k_{TOA}}$ and $\rho_{ld}|_{k_{TOA}}$, which is a function of the true TOA position index k_{TOA}. By taking the expectation of uniform r.v. k_{TOA}, the cost function (f_{cost}) for the error detection (early and late) of TOA path is

$$f_{cost} = \mathbb{E}_{k_{TOA}}\left(P_{ed}|_{k_{TOA}} \cdot \rho_{ed}|_{k_{TOA}} + P_{ld}|_{k_{TOA}} \cdot \rho_{ld}|_{k_{TOA}}\right) \tag{11}$$

If the mean absolute error (MAE) is used to assess the performance of TOA estimator, the estimated TOA index is $\hat{k}$, then the cost for early and late detection is $\rho_{ed}|_{k_{TOA}} = k_{TOA} - \hat{k}$ and $\rho_{ld}|_{k_{TOA}} = \hat{k} - k_{TOA}$, respectively. The total MAE of TOA is

$$\begin{aligned} MAE = \mathbb{E}_{k_{TOA}}\left(P_{ed}|_{k_{TOA}} \cdot (k_{TOA} - \hat{k})\right) + \\ \mathbb{E}_{k_{TOA}}\left(P_{ld}|_{k_{TOA}} \cdot (\hat{k} - k_{TOA})\right) \end{aligned} \tag{12}$$

Direct analysis of the general expression of (12) for TOA estimation is too complicated, not to say obtaining the TOA threshold by minimizing the MAE value. Other approaches determining the threshold only based on the early detection probability [1], [10], [13] may suffer performance loss for its no consideration of signal-to-noise ratio (SNR). We proceed to consider a simplified approach to determine the TOA decision threshold by assuming the cost $\rho_{ed}|_{k_{TOA}} = \rho_{ld}|_{k_{TOA}} = 1$, i.e., directly minimizing the error detection probability. Since, $p(\eta, \sigma_T)$ and $p(\eta, s_T, \sigma_T)$ is the function of η, s_T and σ_T, by taking the expectation of uniform r.v. k_{TOA}, the total error detection probability P_{err} is a function of η, s_T and σ_T as

$$\begin{aligned} P_{err}(\eta, s_T, \sigma_T) &= \mathbb{E}_{k_{TOA}}(P_{ed}|_{k_{TOA}} + P_{ld}|_{k_{TOA}}) \\ &= 1 - \frac{p(\eta, s_T, \sigma_T) - (1 - p(\eta, \sigma_T))^{K_T} p(\eta, s_T, \sigma_T)}{K_T p(\eta, \sigma_T)} \end{aligned} \tag{13}$$

Since the estimated mean value for χ^2 r.v. of T_k is $E_s = \nu\sigma_T^2 + s_T$ and $E_n = \nu\sigma_T^2$ in signal and noise region. Then, the unknown parameter s_T and σ_T in (13) can be obtained by $s_T = E_s - E_n$, $\sigma_T^2 = E_n/\nu$. Then, the optimized TOA threshold can be written as

$$\hat{\eta} = \arg\max_{\eta} P_{err}(\eta, s_T, \sigma_T) := f_\eta(E_s, E_n) \tag{14}$$

Using the threshold crossing method [1], the TOA path can be determined by searching the first sample that crossing the threshold as

$$\hat{\tau}_{TOA} = T \cdot \min_k(k | T_k > \hat{\eta}) - \frac{1}{2}T \tag{15}$$

If 'no level crossing' event occurs, such miss-detection event can be compromised by using the position of estimated signal region $\Re^s$ as the TOA value, and making $\hat{\tau}_{TOA}/T < K_T$, K_T is the maximum accessible TOA index value.

C. Tri-level Sampling Receiver

We assume uniform quantization for the unknown sign of signal, and all the even-level quantizer equipped with threshold of 'zero'. Since we are more interested in low-bit sampling techniques, we choose 1bit, 2bit(4-level) and 3-level case as example, while the 1bit case uses fixed threshold of zero. Fig. 1 shows the maximum fisher information (J_s) for signal estimation, and the corresponding fisher information for noise (J_n) by using optimized quantization threshold. The J_s of 2bit is higher than 3-level case, but with the same value of 0.64 when signal level is high. The information loss of 1bit is more significant than 2bit and 3-level cases, especially when signal level is high. Further, the nonexistence of threshold 'zero' causing significant quantization loss of noise for 3-level ADC. The performance of 3-level quantizer approaches to the more complex 2bit one in high signal regions, and can degrade the noise significantly. For this reason, we consider the 3-level sampling receiver throughout this paper for its simple implementation, and aim to use practical post-quantization processing schemes to improve its performance. The whole procedures works as follows:

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1) Initialize the quantization threshold θ_n.
2) Obtain $N_k^{l_n}$ for each quantization level from N_t transmitted symbols, where $n = 1, 2, 3$.
3) Calculate $\hat{\sigma}$ and $\hat{s}$ using (7) and (8). Obtain the quantization step Δ_{opt} by (5), and then update the quantization threshold θ_n by using (6).
4) Determine the suboptimal decision vector T_k by (10).
5) Perform sliding window detection to estimate signal ($\Re^s$) and noise ($\Re^n$) region; Calculate the first moment (E_s and E_n) of T_k in the two regions; Obtain the TOA decision threshold $\hat{\eta}$ of (14).
6) Perform TOA decision by (15), and obtain the TOA value of $\hat{\tau}_{TOA}$.

In practice, (5) and (14) can be obtained by numerical method, and using a lookup table in real-time systems. To reduce the complexity, the step 3) of quantization threshold only need to be updated for one time, since the SNR condition would not change too much for a given time. Moreover, the whole process does not need complex mathematical operations, and uses all practical structures, which is being implementable with state-of-art technologies.

IV. Numerical and Simulation Result

We use the mean absolute error (MAE) to assess the TOA estimation performance for various sampling approaches. The CM1 channel model of IEEE802.15.4a has been considered throughout the comparison. Channel realization are sampled at 8GHz with 8000 distinct realizations generated; each of which

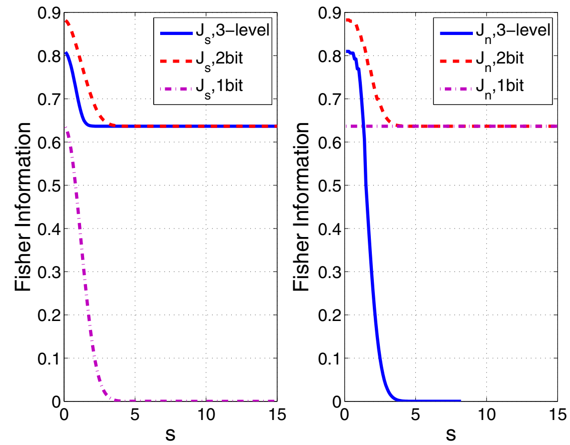

Fig. 1. Fisher information of signal (J_s) and noise (J_n) for 1bit, 2bit and 3-level quantization under different signal s ($\sigma = 1$).

has a TOA uniformly distributed within [0,K_T], $K_T = 800$, and sampled at 8GHz ($T = 0.125ns$), the transmitted pulse width is 0.7ns.

Fig. 2 and Fig. 3 show the comparison of typical low-level sampling receivers for its TOA performance, i.e., 2-level(1bit), 3-level, 4-level(2bit) and full-resolution (FR) sampling receiver. Fig. 2 shows the MAE of different approaches vs. accumulation period N_t, while Fig. 3 focuses on the MAE with different input E_b/N_0. Increasing the accumulation period or input E_b/N_0 can all improve the input SNR and lower the MAE of TOA estimation, also provide us opportunities to assess the superiority of different approaches. The Full-Resolution Matched-Filter (FR-MF) receiver is used as the benchmarking performance for comparison, which cannot be achieved since the signal and channel characteristics are unknown. The postfix of '-fix' in '2bit-fix' and '3-level-fix' means it uses fixed quantization threshold ($\theta = 0.5\sigma$), while '2bit' and '3-level' use the optimized quantization threshold of (5). On the basis of '3-level', the suboptimal weighting scheme (10) is applied to '3-level-weight'. The TOA threshold of these method is chosen as $\eta = 0.15(V_s - V_n) + V_n$, where V_s and V_n is the maximum value in the whole region and noise region. On the basis of '3-level-weight' case, '3-level-all' case uses the optimized TOA threshold of (14), which means it contains all of our proposed performance-improving techniques.

From Fig. 2 and Fig. 3, we know that the MAE of '2bit' and '3-level' is smaller than '2bit-fix' and '3-level-fix', especially in high SNR regions. Thus, we know that using optimized quantization threshold, the performance improvement is significant. The '2bit' case is better than '3-level' with insignificant superiority. It is also the reason that we prefer '3-level' sampling receiver for its simplicity and satisfactory performance; increasing the complexity by 50% to achieve very little benefit is not a wise decision.

The better performance of '3-level-weight' than '3-level' case in Fig. 2 and Fig. 3 demonstrates the benefit of using suboptimal weighting. Though suboptimal of the weighting

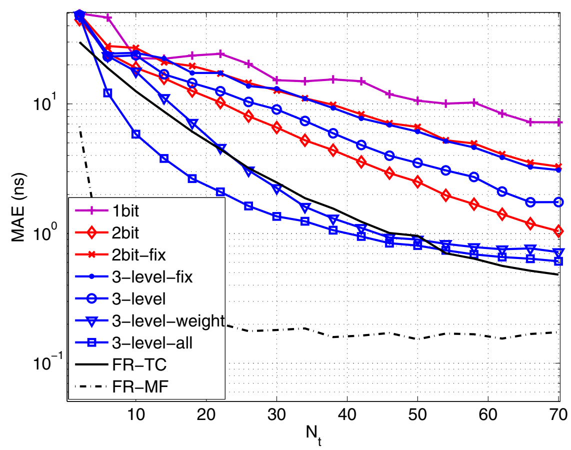

Fig. 2. MAE of TOA estimation using quantized samples for different receivers vs. accumulation period N_t ($E_b/N_0 = 12dB$).

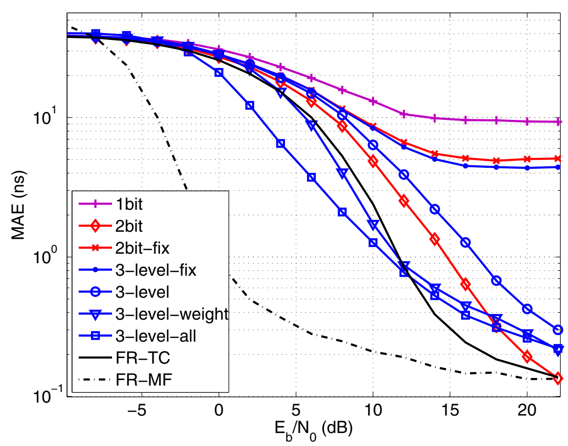

Fig. 3. MAE of TOA estimation for different sampling receiver under CM1 vs. E_b/N_0 ($N_t = 50$).

coefficients (10), the performance improvement is still satisfactory. Setting the TOA decision threshold by minimizing the error detection probability can further improve the TOA performance than conventional TC method, which can be shown by '3-level-all' case in Fig. 2 and Fig. 3. The '3-level-all' even surpasses the 'FR-TC' method in low SNR regions by using all the performance-improving approaches. Note that, the low-bit sampling techniques may suffer more signal loss in high SNR regions, so that our proposed '3-level-all' method cannot surpass the 'FR-TC' case when input $E_b/N_0 > 12dB$ or accumulation period $N_t > 50$.

V. Conclusion

In this paper, the effect of ADC resolution on the performance of TOA estimator is investigated. A scheme which includes three performance-improving methods, i.e., optimized quantization threshold, suboptimal weighting, and optimized TOA decision threshold, is proposed and provides sufficient performance gains for finite-level receivers. Simulations are conducted in several situations with different training pulse numbers, transmitted E_b/N_0's, and sampling approaches, either using the proposed post-quantization processing methods or not. We give the design of the tri-level receiver with the proposed scheme and demonstrate that its performance approaches the conventional TC-based full-resolution receiver. Furthermore, we show that the proposed tri-level receiver is feasible with low-cost and low-power requirements. The simplified signal quantization technique makes a great improvement of the system in terms of the economic competence and the performance.

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