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Joint estimation of Time Of Arrival and Power Profile for UWB Localization

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***Abstract*—In time of arrival (TOA) estimation of received ultra-wideband (UWB) pulses, traditional maximum likelihood (ML) and generalized likelihood estimators become impractical due to their high sampling rate. Sub-nyquist ML-based TOA estimation currently assumes *a priori* knowledge of the UWB channels in the form of the average power delay profile (APDP). In this paper, instead of assuming a known APDP, we propose and investigate a joint estimator of the TOA and the APDP. A parametric model is assumed for the APDP and its parameters are estimated via a least-squares approach; the estimated APDP is then used to find the TOA estimate. The proposed method requires low sampling rate and is well-suited for real-time implementation. Simulation results show that it can achieve a fine accuracy in practical UWB TOA estimation scenarios.**

***Index Terms*—Ultra-wideband (UWB) pulse signals, time of arrival (TOA) estimation, average power delay profile (APDP), source localization, radio frequency identification (RFID).**

I. Introduction

Radio frequency identification (RFID)-based localization allows an object or person to be identified and located using a radio wave exchange [1] between an RFID transmitter (tag) and multiple RFID receivers (tag readers). The spatial coordinates of the RFID tag are calculated by triangulation based on time-of-arrival (TOA) measurements from the tag readers. Therefore, RFID localization heavily relies on accurate algorithms for TOA estimation of the received signals [2]. Ultra-wideband (UWB) impulse-radio (IR) communications, which are based on the transmission of short-duration pulses (typically a few tens to hundreds picoseconds in duration) are particularly suitable for localization system. Indeed, due to their large bandwidth, UWB pulse signals allow fine time resolution, resulting in accurate 3D positioning in indoor localization applications [3]. Furthermore, their carrier-less nature removes the need of up/down conversion and RF mixing stages, leading to simple transceiver designs.

The TOA measurements can be absolute or differential: In the first case, TOAs are measured relative to a clock reference common to all receivers and transmitter, while in the second case, one of the received signals is used as a reference and only the time differences of arrival (TDOA) of the other signals w.r.t. the selected reference are measured. In this work, we focus on the former situation, i.e., absolute TOA estimation, and assume that a suitable clock reference is available at the receivers. Traditional UWB TOA estimators are based on correlation or matched filtering (MF), and select as the TOA estimate the location of the peak MF output power. However, these approaches exhibit poor accuracy in multipath environments because it is highly unlikely that the peak MF output will correspond the first (shortest) arrival path [4].

Multipath propagation was explicitly considered in [5] where the maximum likelihood (ML) TOA estimator was derived and its performance was shown to approach the cramer-rao bound (CRB) at high signal-to-noise ratios (SNRs). The high implementation complexity, however, of the ML estimator limits its practical use. To reduce complexity, the generalized maximum likelihood (GML) estimator was proposed in [6]. The main assumption in the GML estimator is that the strongest path has been correctly acquired. The TOA estimate is obtained as the location of the last path found to be above a predetermined threshold during a backward search starting from the strongest path location. In [7], an improved generalized maximum likelihood (IGML) estimator was proposed, based on the *a priori* knowledge of the average power delay profile (APDP) related to the identified channel condition.

The above approaches assume that the received signals are sampled at the nyquist rate, which for UWB systems, translates into impractically high sampling rates and prohibitive implementation costs. Accordingly, there has been much interest recently into TOA estimation approaches that require lower sampling rates. Among these, estimators based on energy detection have received much attention because of their low complexity. For example, [8] proposed a two-step approach whereby a coarse TOA estimate is first obtained based on energy detection, and then refined via hypothesis testing. The main drawback of TOA estimation based on energy detection is that it suffers greatly from noise and its performance thus degrades rapidly at lower SNR. ML estimators based on sub-nyquist sampling models have also been proposed recently, including the maximum energy sum selection (MESS), weighted maximum energy sum selection (W-MESS) and double-weighted maximum energy sum selection (DW-MESS) [9]. To operate properly, these ML type of estimators generally require *a priori* information about the channel, i.e APDP, which should be estimated beforehand.

In this work, considering that *a priori* knowledge of the UWB channel in the form of the average power delay profile (APDP) may not be available, we propose to jointly estimate the APDP in real-time along with the desired TOA. To this end, an exponential model is assumed for the APDP and its parameters are estimated via a least-squares approach; the estimated APDP is then used to find the TOA estimate via an ML criterion. While maintaining a low sampling rate at the receiver, the proposed joint estimator reaches a high TOA estimation accuracy and outperforms existing ML based sub-nyquist estimators. The proposed method has reasonable complexity and is well-suited for real-time implementation. Simulation results show that it can achieve a fine accuracy in practical UWB TOA estimation scenarios.

The remainder of this paper is organized as follows. Section 2 gives a description of the system model. The PDP estimation and corresponding timing estimator are derived in Section 3. Performance comparisons are provided in Section 4 and a summary is given in Section 5.

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II. System Model

In practical systems such as the ones based on IEEE 802.15.4a standard [10], timing acquisition is commonly performed during the preamble section [11] where no actual data are being transmitted. Each preamble of duration T is divided into N sub-intervals of duration T_f, called frames, such that $T = NT_f$. Each frame is further divided into N_c chips of duration T_c, i.e. $T_f = N_cT_c$. In the jth frame, $j = 0, \ldots, N-1$, a single IR pulse is transmitted at the chip specified by the jth element of the time hopping sequence, denoted by $c_j \in \{0, \ldots, N_c - 1\}$. More specifically, the transmitted signal is given by

$$s(t) = \sum_{j=0}^{N-1} d_j \sqrt{E_p}\, w(t - jT_f - c_jT_c), \quad 0 \le t \le T \tag{1}$$

where $w(t)$ is the unit-energy IR pulse with duration T_c (we assume that the chip and pulse durations are identical), E_p is the energy per pulse and the $d_j \in \{+1, -1\}$ is the jth element of a polarity code sequence used for spectrum smoothing. Both sequences c_j and d_j are assumed known to the receiver. We note that, since we consider the single user case, no time hopping code will be used; without loss in generality, we therefore set $c_j = 0\ \forall j$.

The transmitted signal propagates through a linear time-invariant radio channel having L paths with resolvable path delay equal to T_c. The impulse response of the channel is given by [8]

$$h(t) = \sum_{l=1}^{L} a_l \delta(t - (l-1)T_c - \tau) \tag{2}$$

where a_l is the amplitude of the lth path and τ is the delay of the first path. To avoid inter-frame interference, to ensure that the channel delay spread plus the pulse duration does not exceed the frame duration, we assume that: $0 \le \tau_{max} \le (N_c - L)T_c$ where τ_{max} is the maximum allowable delay for the first path. The path amplitude vector $\boldsymbol{h} = [a_1, ..., a_L]^T$ is modeled as a gaussian random vector with zero mean and covariance $\boldsymbol{R}_h = E\{\boldsymbol{h}\boldsymbol{h}^T\}$ given by [12]

$$\boldsymbol{R}_h = \begin{bmatrix} P_1 & \ldots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \ldots & P_L \end{bmatrix} \tag{3}$$

where the sequence $P_l = E\{a_l^2\}$, $l = 1, \ldots, L$. constitutes the average power delay profile (APDP) of the channel. In this work, we focus on dense multipath channels with an exponentially decaying APDP described by

$$P_l = be^{-la} \tag{4}$$

for some positive values of a and b, where a is the decaying factor and b is a scale parameter.

For the above transmitted signal and propagation channel models, the received signal can be expressed as

$$r(t) = \sum_{l=1}^{L} a_l s(t - (l-1)T_c - \tau) + n(t), \quad 0 \le t \le T \tag{5}$$

where $n(t)$ is an additive noise term modeled as a white gaussian process with zero mean and variance σ_n^2.

For the purpose of deriving the proposed TOA estimator, we consider here a discrete-time version of the signal model in (5) based on uniform sampling at the nyquist-rate $1/T_s$, where $T_s = \frac{1}{2B}$ and B is the bandwidth of transmitted IR signal. Let $M = T_c/T_s$ be an integer, so that each frame is represented by MN_c samples and let $\mathbf{r}_j = [r(jT_f + T_s), \ldots, r(jT_f + MN_cT_s)]_s^T$ denote the column vector of discrete-time noisy signal samples of the jth frame. Similarly, the IR pulse $w(t)$ can be represented by M samples in terms of the column vector $\boldsymbol{w} = [w(T_s), ..., w(MT_s)]^T$. While nyquist-sampling is needed to derive an accurate yet computationally tractable form for the associated log-likelihood function for the problem at hand, the proposed estimator will only require the evaluation of this function at the (sub-nyquist) chip rate of $1/T_c$. Accordingly, it is sufficient to sample the search parameter τ in steps of T_c: that is, we let $\tau = DT_c$ where integer D is the quantity we want to estimate. From the above considerations on τ_{max}, it follows that $0 \le D \le D_{max} \triangleq N_c - L$.

The vector of noisy signal samples $\mathbf{r}_j$ can be written in terms of D as

$$\boldsymbol{r}_j = d_j \sqrt{E_p} \boldsymbol{W}\boldsymbol{h} + \boldsymbol{n}_j \tag{6}$$

where $\boldsymbol{W} = [\boldsymbol{w}_D, \boldsymbol{w}_{D+1}, \ldots, \boldsymbol{w}_{D+L-1}]$ is a $MN_c \times L$ matrix with columns $\boldsymbol{w}_d = [\underbrace{0, \ldots, 0}_{dM}, \boldsymbol{w}^T, \underbrace{0, \ldots, 0}_{N-M-dM}]^T$, $d = D, D+1, \ldots, D+L-1$. Finally, $\boldsymbol{n}_j$ is the discrete-time representation of the noise $n(t)$ in the jth frame. Since $\boldsymbol{h}$ is a gaussian random vector with zero mean and covariance $\boldsymbol{R}_h$, independent of the noise vector $\boldsymbol{n}_j$, it immediately follows that the vector $\boldsymbol{r}_j$ in (6) is also gaussian with zero mean and covariance matrix $\boldsymbol{R}_r = E_p\boldsymbol{W}\boldsymbol{R}_h\boldsymbol{W}^T + \sigma_n^2\boldsymbol{I}$.

III. Time of Arrival Estimation

The log-likelihood function of the received vectors $\boldsymbol{r}_j$, $j = 0, \ldots, N-1$, parameterized with respect to the unknown parameters $P_1, \ldots, P_L$ and D, is given by

$$L(P_1, \ldots, P_L, D) = -\sum_{j=0}^{N-1} \boldsymbol{r}_j^T \boldsymbol{R}_r^{-1} \boldsymbol{r}_j - N \ln(\det(\boldsymbol{R}_r)). \tag{7}$$

For simplicity in presentation, in the above equation we do not explicitly show the dependence of $\boldsymbol{R}_r$ on $P_1, \ldots, P_L$ nor the dependence of $\boldsymbol{W}$ on D.

The unknown parameters can be estimated by maximizing (7). To obtain the estimate of the APDP we first fix D and then we differentiate (7) with respect to $\boldsymbol{R}_h$ to obtain

$$\frac{\partial L}{\partial \boldsymbol{R}_h} = E_p \sum_{j=0}^{N-1} \boldsymbol{W}^T\boldsymbol{R}_r^{-1}\boldsymbol{r}_j\boldsymbol{r}_j^T\boldsymbol{R}_r^{-1}\boldsymbol{W} - E_pN\boldsymbol{W}^T\boldsymbol{R}_r^{-1}\boldsymbol{W}. \tag{8}$$

Setting the derivative to zero, we obtain a conditional form of the ML ADPD estimate as

$$\hat{P}_l^{(0)} = \frac{1}{E_p}\Big(\frac{1}{N}\sum_{j=0}^{N-1} z_{j,l}^2 - \sigma_n^2\Big), \quad l = 1, \ldots, L, \tag{9}$$

where $z_{j,l}$, is the lth element of the vector $\boldsymbol{z}_j \equiv \boldsymbol{z}_j(D) = \boldsymbol{W}^T\boldsymbol{r}_j$. In other words, $z_{j,l}$ is the output of a filter matched to $\boldsymbol{w}_{D+l-1}$ with input the received signal $\boldsymbol{r}_j$ at the jth frame.

Ideally, our APDP estimates in (9) would conform to the exponentially decaying model of (4), i.e., there would exist positive values of the parameters a and b such that

$$\hat{P}_l^{(0)} = be^{-la} \tag{10}$$

or, equivalently,

$$\ln \hat{P}_l^{(0)} = \ln b - la. \tag{11}$$

However, this is not the case in practice. In this paper, we propose to refine our APDP estimates through a least squares fit approach based on (11). We favor the use of (11) instead of (10) because the former is a linear function of the regression parameters a and $\ln b$.

More specifically, we first obtain values for the parameters a and b in (11) that best fit the estimated APDP in a least squares sense, i.e., we obtain a and b by solving the following optimization problem:

$$\min_{a,b} \sum_{l=1}^{L} |\ln \hat{P}_l^{(0)} - (\ln b - la)|^2. \tag{12}$$

The solution to (12) is given by

$$\hat{a} = -\frac{12(\sum_{l=1}^{L} l \ln \hat{P}_l^{(0)}) - 6(\sum_{l=1}^{L} \ln \hat{P}_l^{(0)})(L+1)}{(L+1)(L-1)L} \tag{13}$$

$$\hat{b} = \exp\left(\frac{a(L+1)}{2} + \frac{1}{L}\left(\sum_{l=1}^{L} \ln \hat{P}_l^{(0)}\right)\right). \tag{14}$$

After obtaining $\hat{a}$ and $\hat{b}$, we refine our APDP estimates as follows

$$\hat{P}_l^{(1)} = \hat{b}e^{-l\hat{a}}. \tag{15}$$

It should be noted that due to the log operation in (11), the objective function in (12) overemphasizes low power paths (small values of $\hat{P}_l^{(0)}$) while, at the same time, tolerates large deviations of $\hat{P}_l^{(1)}$ from $\hat{P}_l^{(0)}$ in the case of high power paths. To circumvent this, we only include the strongest paths instead of all L paths in the summation of (12). One simple way to do this is by keeping the paths that are above a predetermined threshold, e.g. 0.1 times of the peak value.

Inserting the refined APDP estimate back into the log-likelihood function, the only unknown parameter left to be estimated is D. Let $L_1(D)$ and $L_2(D)$ stand for the first and the second term in the right-hand side of (7). It can be shown that these terms are equal to

$$L_1(D) = \frac{E_p}{\sigma_n^4} \sum_{j=0}^{N-1} \boldsymbol{z}_j^T \left(\hat{\boldsymbol{R}}_h^{-1} + \frac{E_p}{\sigma_n^2} \boldsymbol{W}^T \boldsymbol{W}\right)^{-1} \boldsymbol{z}_j + C_1 \tag{16}$$

and

$$L_2(D) = -N \sum_{l=1}^{L} \ln\det\left(\frac{E_p \hat{P}_l^{(1)}}{\sigma_n^2} \boldsymbol{w}\boldsymbol{w}^T + \boldsymbol{I}\right) + C_2 \tag{17}$$

where $\hat{\boldsymbol{R}}_h = \text{diag}(\hat{P}_1^{(1)}, \ldots, \hat{P}_L^{(1)})$ and C_1, C_2 are constants. Finally, the delay D is estimated as the integer value which maximizes the likelihood function

$$L_3(D) = \frac{E_p}{\sigma_n^4} \sum_{l=1}^{L} \frac{\hat{P}_l^{(1)} \sum_{j=0}^{N-1} z_{j,l}^2}{1 + \frac{E_p \hat{P}_l^{(1)}}{\sigma_n^2}} - N \sum_{l=1}^{L} \ln\det\left(\frac{E_p \hat{P}_l^{(1)}}{\sigma_n^2} \boldsymbol{w}\boldsymbol{w}^T + \boldsymbol{I}\right) \tag{18}$$

where, we recall, $\hat{P}_l^{(1)}$ and $z_{j,l}$ are function of D. The final likelihood expression $L_3(D)$ only needs the MF outputs $z_{j,l}$, while the background noise variance σ_n^2 can be obtained from *a priori* estimation and the covariance matrix of the transmitted pulse, i.e. $\boldsymbol{w}\boldsymbol{w}^T$, can be pre-computed and stored. In practice, sampling of $\boldsymbol{r}(t)$ at the nyquist rate is not required as the MF outputs $z_{j,l}$ satisfy

$$z_{j,l} = \frac{1}{T_s} \int_0^{T_c} r(jT_f + (D + l - 1)T_c + t) w(t) dt. \tag{19}$$

Therefore, the quantities $z_{j,l}$ corresponding to all candidate values of D can be obtained by computing the correlation integrals of the received signal in each frame with the transmitted pulse (known at receiver) at consecutive intervals of T_c. The accuracy of the estimate so obtained can be further improved via interpolation of the sub-nyquist samples or by a fine search around $\hat{D}$.

IV. Numerical Results

A. Simulation Setup

In the simulations carried out here, and in reference to (7), the preamble of duration $T = 6\mu$s is divided in $N = 30$ frames of duration $T_f = 200$ns, each frame being further divided into $N = 200$ chips of duration $T_c = 1$ns. The transmitted UWB pulse $w(t)$ is a gaussian doublet with unit energy, duration T_c and effective bandwidth $B = 4$GHz. The energy per pulse E_p is given in terms of the SNR parameter E_p/σ_n^2. The channel impulse responses are based on the IEEE 802.15.4a standard channels CM1 through CM4, with the number of taps set to $L = 120$. The channel impulse responses are based on the typical channels CM1 through CM4 described in the IEEE 802.15.04a channel model. The number of channel taps is set to $L = 120$. On the receiver side, the received noisy signal is passed

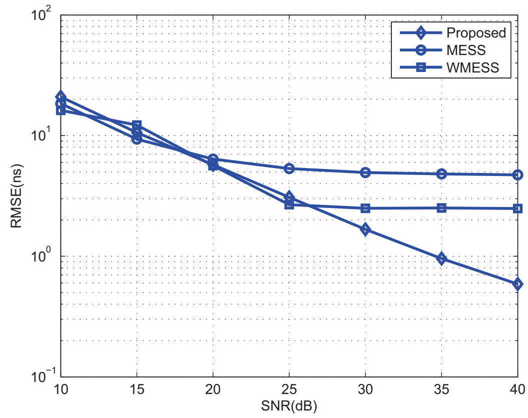

Fig. 1. RMSE of TOA estimator versus SNR for CM1 channel.

through a filter matched to a local copy of the transmitted reference $w(t)$ and sampled at the sub-nyquist rate $\frac{1}{T_c}$, so that both the matched filter integration period and sampling interval are equal to T_c. The sub-nyquist matched filter outputs are used as input variables in the computation of the ML estimator of τ and P_l presented in Section III. The uncertainty region (search range) of the integer delay D is $\{1, \ldots, N_c - L\}$. The TOA estimate, $\hat{D}$, is selected as the one that maximize the likelihood function in (18), with the value of $\hat{P}_l^{(1)}$ given by (15). The proposed method is also compared with other ML based sub-nyquist approaches, including MESS and WMESS [9]. The window lengths for these methods are respectively set to 30ns and 100ns, while an energy receiver is used. The other parameters remain the same as mentioned above.

In the WMESS method, which requires knowledge of the ADPD, we use the exact profile, which puts this method at advantage. The performance of the various TOA estimators is evaluated in terms of their root mean square error (RMSE), defined as $\sqrt{E[(\hat{\tau} - \tau_0)^2]}$ where τ_o denotes the true value of the delay. In the simulations, the expected value is approximated by averaging over 600 independent trials. The quality of the APDP estimator in (15) also be investigated.

B. Performance Comparisons

Fig. 1 provides a comparison of the 3 methods under evaluation for the CM1 channel. It is seen that the proposed method can achieve a better accuracy than previous ML based sub-nyquist estimators, specially at high SNR, where our method can provide less than 1 ns accuracy. Furthermore, while WMESS needs *a priori* knowledge

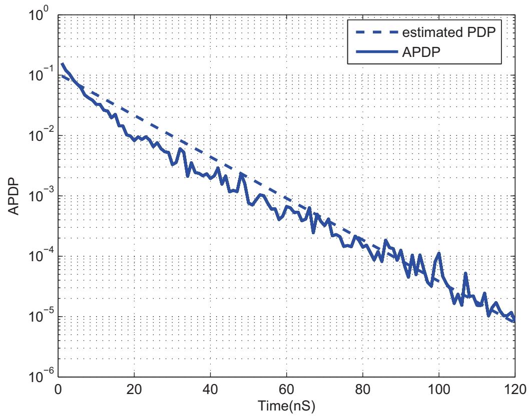

Fig. 2. Estimated power delay profile (CM1 channel, SNR = 40dB).

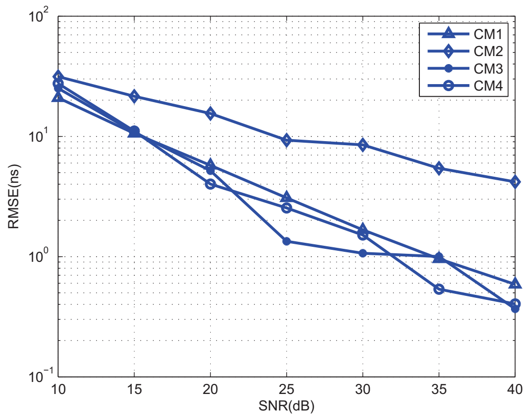

Fig. 3. RMSE of proposed TOA estimator versus SNR for different channels.

of the APDP, our approach can estimate the latter in real-time. To support this claim, Fig. 2 depicts the measured APDP and its estimate based on (15) for the correct delay, in the case of a CM1 channel with SNR=40dB. We note that the estimated APDP in Fig. 2 is based on a particular channel realization; in practice, the quality of the estimation may vary according to the conditions of the current channel impulse response. Fig. 3 compares the RMSE behavior of the proposed estimator as a function of SNR for different IEEE 802.15.04a channel models. From these results, we conclude that the proposed estimator can achieve a better performance in the office environments (CM3, CM4) than residential ones (CM1, CM2). We also note that estimates obtained with line-of-sight (LOS) channels (CM1, CM3) have smaller RMSE values than for the corresponding NLOS channels.

V. Conclusion

We proposed and investigated a joint sub-nyquist ML-based estimator of the TOA and ADPD for applications to UWB impulse radio applications. A parametric model was assumed for the ADPD and its parameters where estimated jointly with the unknown TOA by exploiting the interplay between the ML and LS approaches. This is in contrast to previous sub-nyquist methods which assume that *a priori* knowledge of the ADPD is available. Through simulations, it has been shown that the proposed TOA estimator has a good accuracy and can outperform earlier methods, specially at high SNR. While the joint estimation of the ADPD adds to the complexity, the increase is still reasonable since all the digital processing is done at the lower chip (sub-nyquist) rate. The accuracy of the proposed TOA estimator can be improved by interpolation or fine search. Also, a better estimation of APDP can be obtained by exploiting the channel diversity available in multiuser scenarios.

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