Impulse Radio Ultra-WideBand Ranging Based on Maximum Likelihood Estimation

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Abstract—We propose a high-resolution ranging algorithm for Impulse Radio (IR) Ultra-WideBand (UWB) communication systems in additive white Gaussian noise. We formulate the ranging problem as a Maximum-Likelihood (ML) estimation problem for the channel delays and amplitudes at the receiver. Then we translate the obtained delay estimates into an estimate of the distance. The ML estimation problem is a non-linear problem and is hard to solve. Some previous works focus on finding alternative estimation procedures, for example by denoising. In contrast, we tackle the ML estimation problem directly. First, we use the same transformation as the first step of Iterative Quadratic Maximum Likelihood (IQML) and we transform the ML problem into another optimization problem that avoids the estimation of the amplitude coefficients. Second, we solve the remaining optimization problem with a gradient descent approach (Pseudo-Quadratic Maximum Likelihood (PQML) algorithm). To demonstrate the good performance of the proposed estimator, we present the numerical evaluations under the IEEE 802.15.4a channel model. We show that our algorithm performs significantly better than previously published heuristics. We also derive a reduced complexity version of the algorithm, which will be implemented on the Xilinx Field-Programmable Gate Array (FPGA) board in the future. We test the approach in a real weak Line of Sight (LOS) propagation environment and obtained good accuracy for the ranging.

Index Terms—Maximum likelihood, pseudo-quadratic maximum likelihood, IR, UWB, ranging.

I. INTRODUCTION

IMPULSE Radio (IR) Ultra-WideBand (UWB), a new carrierless communication scheme using impulses, is a candidate technology for future communication and ranging applications. Recent progress on both the technical and regulatory side of this technology has made this possible [1][2][3]. The fine time resolution of UWB signals has created a vision of novel ranging and positioning applications to augment existing narrowband systems operating in dense multipath environments [4][5][6]. Cheong et al evaluate a non-coherent UWB system, which is suitable for low complexity, cost, and data rate UWB wireless sensor networks with positioning

capability in [7]. The results show the possibility of attaining a sub-meter performance using a low complexity and inexpensive device.

Time of Arrival (ToA) estimation is used in range-based localization, by obtaining the distance between the transmitter and receiver from the time-of-flight of the signal [8][9]. Once the distance of an object to at least three reference points are measured, its position can be calculated.

Typical approaches for IR UWB ranging in the literature are based on computing the correlation between the received signal and a reference signal. The peak algorithm takes the corresponding time of the maximum value of correlation as ToA [10]. This algorithm has limited ToA precision, as the strongest path is not necessarily the first arriving path. The leading edge algorithm can determine the leading edge of a received signal, but it depends on operating a high Signal to Noise Ratio (SNR) and an accurate threshold [10]. Lee and Scholtz propose to use a Generalized Maximum Likelihood (GML) approach to search the paths prior to the strongest path [11][12]. In [13], an algorithm takes the average of the received pulses over multiple repetition intervals and correlated the averaged signal with a template. ToA is derived as the corresponding time of the maximum value of correlation. The Ranging problem can also be formulated as an estimation problem for the channel delays and attenuations at the receiver. Ranging is obtained by translating the obtained delay estimates into an estimate of the distance. In [14], Li et al use the Multiple Signal Classification (MUSIC) super-resolution algorithm in frequency-domain channel measurement data to obtain the ranging information. Jativa et al use a Generalized Likelihood Ratio Test (GLRT) to detect the first arriving path from the estimated channel observations in a multipath environment with severe Non-Line of Sight (NLOS) conditions in [15]. In [16], Lottici et al propose a Maximum Likelihood (ML) approach to estimate the channel based on Rake receiver. The algorithm is applied to two different scenarios: either with known training symbols or with unknown ones. Another ToA estimation algorithm implementing a conventional threshold-based estimator and three algorithms implementing an ML estimator based on a peak detection process are studied in [17]. Rabbachin et al propose a ML ToA estimation strategy based on an energy detection approach utilizing a relatively long integration window in [18]. This technique offers improved estimation accuracy and overcomes the practical hardware limitation associated with the need for very short integration times in the receiver. Stoica et al examine the performance of ToA

Manuscript received June 6, 2008; revised November 23, 2008 and April 8, 2009; accepted May 15, 2009. The associate editor coordinating the review of this paper and approving it for publication was M. Torlak.

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This paper was partially presented in International Symposium on Signal Processing and its Applications (ISSPA) 2007 and International Conference on Ultra-WideBand Systems (ICUWB) 2007.

Digital Object Identifier 10.1109/TWC.2009.12.080748

position estimation techniques as well as the simulated and measured performance of an IR-UWB noncoherent energy-collection receiver in [19]. They compare the performance of two different algorithms, namely, the threshold-crossing and the MAXimum selection (MAX) algorithms, in terms of ToA estimation error in Saleh-Valenzuela channel model 3 and channel model 4. They also present the implemented structure of the ToA MAX algorithm suitable for IR-UWB-based noncoherent receivers. In [20], a framework, simple enough to allow a tractable analysis and provide insights that could be valuable in the design of practical UWB systems subject to interference, is proposed. Molisch *et al* propose a two-step ToA estimation algorithm in [21]. In order to accelerate the estimation process, the first step estimates a rough ToA of the received signal based on received signal energy. Then, in the second step, the arrival time of the first signal path is estimated by considering a hypothesis testing approach. The proposed scheme uses low-rate correlation outputs and is able to perform accurate ToA estimation with reasonable time intervals. In addition, IR UWB can be used in the scenario of vehicular sensor networks [22]. For example, Li *et al* carry out an original work for traffic monitoring with vehicular sensor networks and the contribution is that they demonstrate the feasibility of this application [23] [24]. In their work, the main issue which influences the accuracy of traffic status estimation algorithm is the performance of the map-matching due to the well-known GPS error [25]. Actually, based on their work, we could apply IR-UWB ranging to assist other localization technologies to improve the traffic estimation algorithm.

In this paper, we consider that ranging is performed by a combination of message exchanges, as for example, described in [26]. Using such a methodology, the receiver expects a signal from the source within a short window of time. The problem then becomes for the receiver to accurately estimate, using its own clock reference, the time of arrival of the expected signal. The received signal is a pulse distorted by a multipath channel. We are looking for a high accuracy solution that works even in weak Line-of-Sight (LOS) propagation environments, for example if we have an obstruction due to small objects.

In this paper, we propose a high resolution IR UWB ranging algorithm. First, we pose the ranging problem as an ML estimation problem for the channel delays and their amplitudes at the receiver. We evaluate the ranging by translating the received delay estimates into an estimate of the distance. The ML estimation problem is non-linear and difficult to solve. Some previous works focus on finding alternative estimation procedures, for example, by denoising [27]. We use an approach where we aim to directly solve the ML estimation as an optimization problem. This is a difficult problem in low SNR cases, or when the LOS component of the signal propagation is weak (weak LOS environments). A direct solution using classical heuristics does not perform well in such cases; indeed, the log-likelihood function has many local minima, and extensive search procedures with many iterations are required. Our first step is to observe that if the channel delays would be known, we would have a linear regression problem, whose solution can be expressed

exactly in a matrix form. This allows us to transform the ML problem into an equivalent problem, but with fewer dimensions (see (19)). Thus, the problem becomes one that fits in the class of problems solved by the Iterative Quadratic Maximum Likelihood (IQML) algorithm [28]. However, we find that this iterative heuristic does not work well in low SNR. Instead, it is possible to use the gradient based approach (Pseudo-Quadratic Maximum Likelihood (PQML) algorithm), of [29] originally used based on a time-domain foundation of the received signal. We find, after its appropriate formulation in the frequency domain, that it reaches the optimum in very few steps. Furthermore, the initialization of the algorithm is performed implicitly (We do not need an explicit initialization using another estimation procedure.). The obtained performance of the proposed ranging algorithm is quasi-optimal because it numerically solves the exact ML problem. To show our algorithm performs significantly better than previously published heuristics, we present the numerical evaluations under IEEE 802.15.4a channel model. We also derive a reduced-complexity version of the proposed algorithm, which will be implemented on a Xilinx Field-Programmable Gate Array (FPGA) board. We test the approach in a real, weak LOS propagation environment and obtained good accuracy for the ranging.

The paper is organized as follows: We explain our approach of the estimation problem in section II. In section III, we transform our ML estimation problem into a pseudo-quadratic formulation. In section IV, we describe our proposed ML algorithm. We analyze the computational complexity in section V. We illustrate simulation results in Section VI. Section VII illustrates the performances of the ranging algorithm under real environments. We give conclusions in section VIII.

II. PROBLEM STATEMENT

In this section, we present the system models in both time- and frequency-domains.

The indoor radio channel's impulse response is given by

$$h(t) = \sum_{l=1}^L \alpha_l \delta(t - \tau_l), \quad (1)$$

where L is the number of multipath components, α_l and τ_l are the amplitude and the propagation delay of the l th path respectively. Much work has been devoted to model the propagation on the UWB channel. In 1972 [30], Turin proposed one model based on clusters of paths. Then in 1987, Saleh and Valenzuela developed a model for the multi-path channel under indoor environments. The Saleh-Valenzuela model provides a useful analysis tool for indoor multipath propagation, where multipath components arrive in Poisson-distributed clusters [31].

In our analysis, the set of delays τ_l and gains α_l are generated according to the models proposed by the IEEE802.15.4a working group for weak LOS environments. However, in the UWB channel model developed in [32], a frequency-dependent path loss model is used to describe the per-path pulse distortion yielding a UWB channel model with complex coefficients. We restrict our analysis to a real-valued UWB channel model where there is no pulse distortion.

An IR UWB pulse with waveform, $p(t)$ of duration T_p , is received through this channel. Typically, a Gaussian pulse or one of its derivatives is used as a UWB pulse. The authors of [33] propose the first, second and fifth derivative of the Gaussian pulse for UWB communications. The theory described here is general admitting arbitrary types of UWB pulses.

The received IR UWB signal can be expressed as

$$y(t) = \sum_{l=1}^L \alpha_l p(t - \tau_l) + z(t), \quad (2)$$

where $z(t)$ is an additive independent white Gaussian noise with zero mean and variance σ_z^2 .

Given a sampling interval, T_s , the discrete time representation of our system becomes:

$$y(kT_s) = \sum_{l=1}^L \alpha_l p(kT_s - \tau_l) + z(kT_s). \quad (3)$$

K samples in the interval $[0, T_o]$ are received, which are concatenated in the vector $\vec{y} = [y(T_s), y(2T_s), \dots, y(KT_s)]^T$ through the transmission of M samples of an IR UWB pulse. The superscript T denotes the transpose operator. We define $\vec{p} = [p(T_s), p(2T_s), \dots, p(MT_s)]^T$, $T_p = MT_s$ and $M < K$.

Hence, the received signal can be expressed as:

$$\vec{y} = \mathbf{W}\vec{\alpha} + \vec{z}, \quad (4)$$

where $\mathbf{W}$ can be defined as following:

$$\mathbf{W} = [\vec{w}^{D_1} \quad \vec{w}^{D_2} \quad \dots \quad \vec{w}^{D_L}]^T,$$

where

$$\vec{w}^{D_l} = [\mathbf{0}_{D_l}^T \quad \vec{p}^T \quad \mathbf{0}_{K-M-D_l}^T]^T,$$

$\mathbf{0}_{D_l}$ denotes the all zeros vector of length D_l and D_l refers to the discretized version of the time delay τ_l that satisfies $\tau_l \simeq D_l T_s$. The columns of the matrix $\mathbf{W}$ represent the sampled replicas of $p(t)$ shifted by delays τ_l for $0 < \tau_1 < \tau_2 < \dots < \tau_L$ and $\tau_L \leq T - T_p$.

When the observation noise is Gaussian, the ML criterion becomes equivalent to a Least Squares (LS) one. It can be shown [34] that the ML estimates of $\vec{\tau}$ and $\vec{\alpha}$ are given by

$$\begin{aligned} \hat{\vec{\tau}} &= \min_{\vec{\tau}} \{ \vec{y}^H P_{\mathbf{W}} \vec{y} \}, \\ \hat{\vec{\alpha}} &= (\mathbf{W}(\hat{\vec{\tau}}))^+ \vec{y}. \end{aligned} \quad (5)$$

where P_A refers to the projection matrix defined by $P_A = (A(A^H A)^{-1} A^H)$ and superscript $+$ denotes the Moore-Penrose pseudo-inverse. The cost function to be maximized in expression (5) does not decouple the vector $\vec{\tau}$ and hence closed-form expression for its estimate, $\hat{\vec{\tau}}$, can't be directly obtained. To do so, we write the expression in (4) in the frequency domain.

Assuming that the received signal has finite energy, we take the Discrete Fourier Transform (DFT) of (3), assuming that N samples of DFT are available for the set of frequencies $\{f_1, f_2, \dots, f_N\}$. We obtain

$$Y(f_n) = \sum_{l=1}^L \alpha_l P(f_n) e^{-j2\pi f_n \tau_l} + Z(f_n), \quad (6)$$

where $Y(f_n)$, $P(f_n)$ and $Z(f_n)$ are the DFT of $y(kT_s)$, $p(kT_s)$ and $z(kT_s)$, respectively, taken at frequency $f_n = \frac{n-1}{N}$ and $n = 1, \dots, N$.

We can rewrite (6) in a matrix form as following:

$$\vec{Y} = \vec{X} + \vec{Z} = \mathbf{S}\mathbf{V}(\vec{\tau})\vec{\alpha} + \vec{Z}, \quad (7)$$

where $\mathbf{S}$ is a $N \times N$ diagonal matrix, $\mathbf{V}(\vec{\tau})$ is a $N \times L$ matrix and $\vec{X}$ is the noiseless received signal, defined as

$$\vec{Y} = [Y(f_1) \quad \dots \quad Y(f_N)]^T,$$

$$\vec{X} = \mathbf{S}\mathbf{V}(\vec{\tau})\vec{\alpha},$$

$$\mathbf{S} = \begin{bmatrix} P(f_1) & & \\ & \ddots & \\ & & P(f_N) \end{bmatrix},$$

$$\mathbf{V}(\vec{\tau}) = [\vec{v}(\tau_1) \quad \dots \quad \vec{v}(\tau_L)]^T,$$

$$\vec{v}(\tau_l) = \begin{bmatrix} 1 & e^{-j\frac{2\pi\tau_l}{N}} & \dots & e^{-j\frac{2\pi(N-1)\tau_l}{N}} \end{bmatrix}^T,$$

$$\vec{\alpha} = [\alpha_1 \quad \dots \quad \alpha_L]^T,$$

$$\vec{\tau} = [\tau_1, \tau_2, \dots, \tau_L]^T,$$

$$\vec{Z} = [Z(f_1) \quad \dots \quad Z(f_N)]^T.$$

The diagonal elements of the matrix $\mathbf{S}$ correspond to the DFT of the IR UWB pulse $\vec{p}$. $\vec{Z}$ is the DFT of the Gaussian noise samples. As the noise is assumed to be white and Gaussian, the elements of $\vec{Z}$ will be additive Gaussian random variables.

The estimation problem is defined as:

- **Given:**

- the received signal $\vec{y}$,
- the transmit pulse $\vec{p}$,
- the number of multipath L .

- **Estimate:**

- estimate the amplitude $\vec{\alpha}$ and the propagation delay $\vec{\tau}$ of the different paths jointly,
- estimate the distance d ($d = \tau_1 \cdot c$, where $c = 3 \cdot 10^8$ m/s) between the transmitter and receiver.

III. THE MAXIMUM LIKELIHOOD ESTIMATION

Under the additive white Gaussian noise assumption, the ML estimate of the $\vec{\tau}$ and $\vec{\alpha}$ is obtained by solving the non-linear LS problem

$$F_{ML}(\vec{\tau}, \vec{\alpha}) = \min_{\vec{\tau}, \vec{\alpha}} \|\vec{Y} - \mathbf{S}\mathbf{V}(\vec{\tau})\vec{\alpha}\|^2, \quad (8)$$

where for a given vector $\vec{h}$, $\|\vec{h}\|$ denotes its Fronebus norm.

Consider that we select $\mathbf{S}\mathbf{V}(\vec{\tau})$, then the best $\vec{\alpha}$ for the given choice of $\mathbf{S}\mathbf{V}(\vec{\tau})$ is obtained by minimizing the expression (8) and we obtain:

$$\hat{\vec{\alpha}} = ((\mathbf{S}\mathbf{V}(\vec{\tau}))^H (\mathbf{S}\mathbf{V}(\vec{\tau}))^{-1} (\mathbf{S}\mathbf{V}(\vec{\tau}))^H \vec{Y}), \quad (9)$$

¹L can be obtained by means of information theoretic criteria as in [35].

where superscript H denotes the Hermitian transpose. Plugging the estimate $\hat{\vec{\alpha}}$ into (8), we obtain the following non-linear estimation problem:

$$F'_{ML}(\vec{\tau}) = \min_{\vec{\tau}} \|(\mathbf{I} - P_{\mathbf{S}\mathbf{V}(\vec{\tau})})\vec{Y}\|^2, \quad (10)$$

where $P_{\mathbf{S}\mathbf{V}(\vec{\tau})} = \mathbf{S}\mathbf{V}(\vec{\tau})((\mathbf{S}\mathbf{V}(\vec{\tau}))^H(\mathbf{S}\mathbf{V}(\vec{\tau}))^{-1}(\mathbf{S}\mathbf{V}(\vec{\tau}))^H)$.

Using the theorem in [36], it can be proved that

$$F_{ML}(\vec{\tau}, \vec{\alpha}) = F_{ML}(\hat{\vec{\tau}}, \hat{\vec{\alpha}}) \approx F'_{ML}(\hat{\vec{\tau}}). \quad (11)$$

We obtain the ML estimate of $\vec{\tau}$ as follows:

$$\hat{\vec{\tau}} = \arg \min_{\vec{\tau}} \vec{Y}^H P_{\mathbf{S}\mathbf{V}(\vec{\tau})}^\perp \vec{Y}, \quad (12)$$

where $P_{\mathbf{S}\mathbf{V}(\vec{\tau})}^\perp$ is the orthogonal projection on the subspace spanned by $\mathbf{S}\mathbf{V}(\vec{\tau})$. If the DFT frequencies, $\{f_1, f_2, \dots, f_N\}$, are chosen, then $\mathbf{V}(\vec{\tau})$ is a Vandermonde matrix. Hence, there exists a Toeplitz matrix, $\mathbf{B}$, of dimension $N \times (N - L)$ such that

$$\mathbf{B}^H \mathbf{V}(\vec{\tau}) = 0, \quad (13)$$

The matrix $\mathbf{B}$ is given by

$$\mathbf{B} = \begin{bmatrix} b_0 & 0 & & & \\ b_1 & b_0 & \ddots & & \\ \vdots & b_1 & \ddots & 0 & \\ b_L & \vdots & \ddots & b_0 & \\ 0 & b_L & \ddots & b_1 & \\ & \ddots & \ddots & \vdots & \\ & & 0 & b_L & \end{bmatrix},$$

and its elements are taken from the coefficients of polynomial

$$x(\nu) = b_0 \nu^L + b_1 \nu^{L-1} + \dots + b_L, \quad (14)$$

with roots equal to $\{e^{-j\frac{2\pi\tau_1}{N}}, \dots, e^{-j\frac{2\pi\tau_L}{N}}\}$. As the roots of this polynomial lay on the unit circle, the coefficients vector $\vec{b} = [b_0, b_1, \dots, b_L]^T$ has the following constraints:

$$\vec{b} \neq 0, \quad (15)$$

$$\vec{b} : b_i = b_{L-i}^*, i = 0, \dots, L, \quad (16)$$

where the superscript $*$ refers to the complex conjugate operation.

From (13), we obtain

$$P_{\mathbf{S}\mathbf{V}(\vec{\tau})}^\perp = P_{\mathbf{S}^{-H}\mathbf{B}}, \quad (17)$$

and hence (13) can be reformulated in terms of $\vec{b}$ rather than $\vec{\tau}$ as:

$$\hat{\vec{b}} = \arg \min_{\vec{b}} \vec{Y}^H \mathbf{S}^{-H} \mathbf{B} \mathbf{R}^{-1} \mathbf{B}^H \mathbf{S}^{-1} \vec{Y}, \quad (18)$$

where $\mathbf{R} = \mathbf{B}^H \mathbf{S}^{-1} \mathbf{S}^{-H} \mathbf{B}$ and $\mathbf{R}$ is a function of $\vec{b}$. Once $\hat{\vec{b}}$ is found by solving (18), $\vec{\tau}$ is obtained by finding the roots of $x(\nu)$ in expression (14).

As $\mathbf{B}^H$ is linear in $\vec{b}^*$, a matrix $\mathbf{E}$ can be found such that $\mathbf{E}\vec{b}^* = \mathbf{B}^H \vec{e}$. $\mathbf{E}$ is filled with the elements of the vector $\vec{e} = \mathbf{S}^{-1} \vec{Y}$. As such, (18) becomes:

$$\hat{\vec{b}} = \arg \min_{\vec{b}} \vec{b}^H \mathbf{E}^T \mathbf{R}^{-1} \mathbf{E}^* \vec{b}. \quad (19)$$

Finding the ML estimate of $\vec{\tau}$ is equivalent to finding $\vec{b}$. Searching $\vec{b}$ is a non-linear minimization problem with linear or quadratic constraints. In the IQML algorithm [28], $\vec{b}$ is searched by an iterative procedure. At each iteration of the IQML procedure, the denominator $\mathbf{R}$, computed using the estimate of the vector $\vec{b}$ obtained in the previous iterations, is considered as constant and hence (19) becomes quadratic. Thus the vector $\vec{b}$ is estimated as the minimal eigenvector of the matrix $\mathbf{E}^T \mathbf{R}^{-1} \mathbf{E}^*$. The IQML algorithm leads to good estimates for high values of the SNR. At low values of the SNR, the IQML approach diverges and the global ML cost function minimum cannot be found. In this paper, we use the PQML algorithm, which was originally formulated in the time-domain aim for the received signal, to find the global ML cost function minimum in the low SNR environments.

IV. PSEUDO-QUADRATIC MAXIMUM LIKELIHOOD ESTIMATION ALGORITHM

In [29], the PQML algorithm was shown to outperform the proposed ML based multi-channel estimation techniques in determining the minimum of ML cost function. Here, we propose here to apply this technique to the time-delay estimation case. The main idea is to arrange the gradient of the ML criterion given by (18) as $\Gamma(\vec{b})\vec{b}$, where $\Gamma(\vec{b})$ is positive semi-definite. The ML solution verifies $\Gamma(\vec{b})\vec{b} = 0$. As such, $\vec{b}^H \Gamma(\vec{b})\vec{b} = 0$. The estimation of $\vec{b}$ is solved using the following PQML approach: in the first step $\Gamma(\vec{b})$ is considered constant, and as $\Gamma(\vec{b})$ is positive semi-definite, the minimization of (18) is equivalent to minimize $\vec{b}^H \Gamma(\vec{b})\vec{b}$, which becomes a quadratic problem. Hence $\vec{b}$ can be estimated from such quadratic criterion and its estimate can be refined iteratively. The key issue is to find the appropriate $\Gamma(\vec{b})$ and in particular with the positive semi-definite constraint. For our estimation problem, the gradient of the ML criterion given by (18), can be written as

$$\Gamma(\vec{b})\vec{b},$$

$$\Gamma(\vec{b}) = \mathbf{E}^T \mathbf{R}^{-T} \mathbf{E}^* - \Psi^H \mathbf{S}^{-1} \mathbf{S}^{-H} \Psi,$$

where the matrix Ψ is defined such that

$$\vec{\psi} = \mathbf{R}^{-1} \mathbf{B}^H \vec{e},$$

$$\mathbf{B} \vec{\psi} = \Psi \vec{b}.$$

In this way, $\vec{b}$ can be estimated based on the following ML criterion:

$$\begin{aligned} \hat{\vec{b}} &= \arg \min_{\vec{b}} \vec{b}^H \Gamma(\vec{b})\vec{b} \\ &= \arg \min_{\vec{b}} \vec{b}^H (\mathbf{E}^T \mathbf{R}^{-T} \mathbf{E}^* - \Psi^H \mathbf{S}^{-1} \mathbf{S}^{-H} \Psi) \vec{b} \\ &= \arg \min_{\vec{b}} \{ \vec{b}^H \mathbf{E}^T \mathbf{R}^{-T} \mathbf{E}^* \vec{b} - \vec{b}^H \Psi^H \mathbf{S}^{-1} \mathbf{S}^{-H} \Psi \vec{b} \}. \end{aligned} \quad (20)$$

The first term of (20) is same with (19). The expectation of the second term in (20) is $\vec{b}^H E\{\Psi^H \mathbf{S}^{-1} \mathbf{S}^{-H} \Psi\} \vec{b} = \text{tr}\{P_{\mathbf{S}^{-H}\mathbf{B}}(E\{\vec{Z}\vec{Z}^H\})\} = \sigma_N^2(N - L)$, where tr stands for the trace of the matrix and E denotes the expectation computation. So the effect of the second term in (20) is to remove the noise in the first term of (20) asymptotically (when N goes to infinity). As N goes to infinity, the ML criterion

in (20) is equivalent to the following de-noised criterion: $\arg \min_{\vec{b}} \vec{b}^H \mathbf{F}^T \mathbf{R}^{-T} \mathbf{F} \vec{b}$, where the matrix $\mathbf{F}$ is filled with the elements of the noiseless received signal $\mathbf{S}^{-1} \vec{X}$ and such that $\mathbf{F} \vec{b}^* = \mathbf{B}^H \mathbf{S}^{-1} \vec{X}$.

For finite N , the matrix $\mathbf{\Gamma}(\vec{b})$ is indefinite and applying directly the PQML strategy will not work except at high SNR values. As originally done using this procedure, we introduce an arbitrary λ in the minimization criterion (20), which becomes

$$\hat{\vec{b}} = \arg \min_{\vec{b}, \lambda} \{ \vec{b}^H (\mathbf{E}^T \mathbf{R}^{-T} \mathbf{E}^* - \lambda \mathbf{\Psi}^H \mathbf{S}^{-1} \mathbf{S}^{-H} \mathbf{\Psi}) \vec{b} \}, \quad (21)$$

with semi-definite positivity constraint on the central matrix. Hence $\vec{b}$ can be found as the minimal generalized eigenvector of $\mathbf{E}^T \mathbf{R}^{-T} \mathbf{E}^*$ and $\mathbf{\Psi}^H \mathbf{S}^{-1} \mathbf{S}^{-H} \mathbf{\Psi}$ and λ is the corresponding minimum generalized eigenvalue. Asymptotically, there is global convergence for $\vec{b}$, which converges to the ML minimizer.

The good estimates for the vector $\vec{b}$ obtained using the PQML technique, will lead to good estimates for the channel delays and amplitudes, $\hat{\tau}$ and $\hat{\alpha}$. In the case of ranging for IR UWB, the parameter we are interested in is $\hat{\tau}_1$, which is the smallest element in the channel delay vector estimate, $\hat{\vec{\tau}}$.

V. COMPLEXITY ANALYSIS

A. Implicit Implementation of Constraints of $\vec{b}$

The implicit implementation of the constraints of $\vec{b}$ in (15) and (16) converts the problem into an unconstrained one and reduces its size by 2.

We introduce $\vec{b}'$ (a $(L+1) \times 1$ vector) and $\mathbf{RI}$ (a $(L+1) \times (L+1)$ matrix). Note that $\vec{b}'$ and $\mathbf{RI}$ have different structures when L is even or odd.

(L) L is even

$$\vec{b}' = \begin{bmatrix} \text{Re}(b_0) & \text{Im}(b_0) & \cdots & \\ \text{Re}(b_{L/2-1}) & \text{Im}(b_{L/2-1}) & b_{L/2} & \end{bmatrix}^T,$$

$$\mathbf{RI} = \begin{bmatrix} 1 & j & 0 & 0 & 0 & \cdots & 0 & 0 & 0 \\ 0 & 0 & 1 & j & 0 & \cdots & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & 0 & \cdots & 1 & j & 0 \\ 0 & 0 & 0 & 0 & 0 & \cdots & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & \cdots & 1 & -j & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 1 & -j & 0 & \cdots & 0 & 0 & 0 \\ 1 & -j & 0 & 0 & 0 & \cdots & 0 & 0 & 0 \end{bmatrix},$$

where $\text{Re}(b_i)$ and $\text{Im}(b_i)$ refer to the real part and image part of b_i respectively. j is defined as $j^2 = -1$.

(2) L is odd

$$\vec{b}' = \begin{bmatrix} \text{Re}(b_0) & \text{Im}(b_0) & \cdots & \\ \text{Re}(b_{(L+1)/2}) & \text{Im}(b_{(L+1)/2}) & & \end{bmatrix}^T,$$

TABLE I
DESCRIPTION OF THE PQML RANGING ALGORITHM

(a) Initialization:
$k = 0$ and set $\mathbf{R}$ in (19) to identity matrix.
$\hat{\vec{b}}_{(0)}$ is equal to the minimal eigenvector of $\mathbf{E}^T \mathbf{E}^*$.
ϵ is chosen according to the desired precision.
(b) Compute the two matrixes in (22):
$C1_{(k)} = \mathbf{R} \mathbf{I}^H \cdot \mathbf{E}^T \mathbf{R}^{-T} \mathbf{E}^* \cdot \mathbf{R} \mathbf{I}$
$C2_{(k)} = \mathbf{R} \mathbf{I}^H \cdot \mathbf{\Psi}^H \mathbf{S}^{-1} \mathbf{S}^{-H} \mathbf{\Psi} \cdot \mathbf{R} \mathbf{I}$
where $\mathbf{R}_{(k)}$ and $\mathbf{\Psi}_{(k)}$ are constructed from $\hat{\vec{b}}_{(k)}$.
(c) Estimate $\hat{\vec{b}}_{(k+1)}$:
$\hat{\vec{b}}_{(k+1)}$ can be found as the minimal generalized eigenvector of $C1_{(k)}$ and $C2_{(k)}$ according to (22).
(d) Check convergence:
$\ \hat{\vec{b}}_{(k+1)} - \hat{\vec{b}}_{(k)} \ < \epsilon$?
Yes - done, go to the next step.
No - $k = k + 1$ and go to step (b) .
(e) Estimate $\hat{\vec{\tau}}$:
$\hat{\vec{\tau}}$ can be found by computing the roots of the polynomial $x(\nu)$ in (14) with $\hat{\vec{b}}_{(k)}$.
(f) Estimate the channel amplitude $\hat{\alpha}$ and ranging $\hat{d}$:
The channel amplitude $\hat{\alpha}$ can be computed by (9)
and ranging $\hat{d} = \hat{\tau}_1 \cdot c$, where $c = 3 \cdot 10^8$.

$$\mathbf{RI} = \begin{bmatrix} 1 & j & 0 & 0 & 0 & \cdots & 0 & 0 \\ 0 & 0 & 1 & j & 0 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & 0 & \cdots & 1 & j \\ 0 & 0 & 0 & 0 & 0 & \cdots & 1 & -j \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 1 & -j & 0 & \cdots & 0 & 0 \\ 1 & -j & 0 & 0 & 0 & \cdots & 0 & 0 \end{bmatrix}.$$

From the above equations, we have $\vec{b} = \mathbf{RI} \cdot \vec{b}'$. Equation (21) becomes

$$\hat{\vec{b}}' = \arg \min_{\vec{b}', \lambda} \{ \vec{b}'^H (\mathbf{R} \mathbf{I}^H \cdot \mathbf{E}^T \mathbf{R}^{-T} \mathbf{E}^* \cdot \mathbf{R} \mathbf{I} - \lambda \cdot \mathbf{R} \mathbf{I}^H \cdot \mathbf{\Psi}^H \mathbf{S}^{-1} \mathbf{S}^{-H} \mathbf{\Psi} \cdot \mathbf{R} \mathbf{I}) \vec{b}' \}. \quad (22)$$

Table I describes our proposed PQML based ranging algorithm for IR UWB transmitted signal in more details.

B. Derivation of a Reduced-Complexity Version of the Proposed Algorithm

Most of the computation work involved in each of the iteration steps is inverting an $(N-L) \times (N-L)$ matrix $\mathbf{R}$. The size of the matrix can be quite large, as the number of DFT, N , is usually significantly larger than L , the expected number of exponentials. The matrix $\mathbf{R}$ is a banded Toeplitz matrix whose structure can be exploited for efficient computation. Thus, the inversion of $\mathbf{R}$ can be replaced by inverting a much smaller $2L \times 2L$ matrix [37].

If we compute the inverse matrix $\mathbf{R}$ directly, the computational complexity will be $O((N-L)^3)$. With the low complexity implementation, the computational complexity of the inversion will decrease to $O(L^3)$. As N is much larger

Fig. 1. IR UWB ranging system architecture.

TABLE II
COMPLEXITY ANALYSIS OF PQML ALGORITHM

Multiplications
$3N^3 + (4 - 6L)N^2 + (5 + 12L^2 + 8L)N + 12L^3 - L^2 - 2L + 2$
Summations
$3N^3 + (1 - 4L)N^2 + (5L^2 + 6L + 1)N + 2L^3 - 3L - 3$

TABLE III
COMPLEXITY ANALYSIS OF IQML ALGORITHM

Multiplications
$N^3 + (3 - 6L)N^2 + (9L^2 + 4L + 3)N + 11L^3 - 4^2 - 5L + 1$
Summations
$2N^3 - 3LN^2 + (4L^2 + 5L + 1)N + L^3 - 3L^2 - 7L - 4$

than L , the computational complexity of the PQML algorithm can be significantly decreased.

The algorithm in [38][39] can compute the smallest generalized eigenvalue and eigenvector of matrixes $C1$ and $C2$ with lower computational complexity, which allow us to not compute all the eigenvalues and eigenvectors.

C. Complexity Analysis

The exact number of operations which does not include the load induced by DFT, for one iteration of the algorithm with low complexity implementation, is given in Table II. In our simulation, the algorithm typically converges in at most 5 iterations.

The exact number of operations for one iteration of IQML is given in Table III. According to [27], the computational complexity of the Subspace algorithm is $O(LN^2)$. Note that, the computational complexity of PQML is slightly higher compared to the other two algorithms. (See Table II).

VI. SIMULATION RESULTS

In this section, we present numerical evaluations of the PQML based ranging algorithm. The performance of the proposed PQML based ranging algorithm is compared to the Subspace algorithm [27] and the IQML algorithm [28].

The IR UWB ranging system can be represented as having three blocks: a transmitter, a channel and a receiver. Fig.1 illustrates the architecture of the IR UWB ranging system. The goal of the ranging receiver is to acquire the signal in order to process it. The received signals, $y(t)$, is first band-pass filtered and then down-converted to a baseband signal with an oscillator-driven mixer. The continuous signal is sampled to obtain a discrete signal. The sampling frequency is greater than two times the frequency band of the band-pass filter. To reduce the effect of the Gaussian noise on the estimation of the IR UWB ranging, the discrete signals are averaged to obtain a reduced-noise signal. The DFT of the discrete signal ($Y(f_n)$ in (6)) is used in the PQML algorithm for ranging as described in Section IV.

The transmitted pulse $p(t)$ is selected as the second derivative of the Gaussian function with duration $T_p = 1\text{ns}$ which is a typical duration of an IR UWB pulse. The bandwidth of the band-pass filter in the receiver is 500 MHz. The sampling frequency is 2GHz. We apply a DFT of length $N = 512$ and the parameter $\epsilon = 10^{-3}$.

The CM1 of the channel IEEE 802.15.4a, a standard for short range Low-Datarate (LDR) Wireless Personal Area Network (WLAN), is used in the simulations to test PQML based ranging algorithm. As we are only interested in the estimation of the first channel delay, only the most significant paths of the CM1 channel are kept and the others are skipped. The distances between the transmitter and the receiver are 3 and 6 meters under CM1 channels, respectively.

The results are averaged over 300 Monte-Carlo trials and for any given trial, the Normalized Minimum Square Error (NMSE) for a vector of parameters is defined by $\frac{\|\vec{a} - \hat{\vec{a}}\|^2}{\|\vec{a}\|^2}$, where $\vec{a}$ refers to the vector of parameters to be estimated. The initialization of the PQML ranging algorithm is performed by setting the matrix $\mathbf{R}$ equal to identity. Note that this

Fig. 2. NMSE of the delay Estimation vs. SNR. The distance between the transmitter and the receiver is 3 meters.

Fig. 4. NMSE of delay estimation vs. SNR. The distance between the transmitter and receiver is 6 meters.

Fig. 3. Ranging error vs. SNR. The distance between the transmitter and receiver is 3 meters.

Fig. 5. Ranging Error vs. SNR. The distance between the transmitter and receiver is 6 meters.

initialization corresponds to the solution of the minimization of the LS problem $\min_b \|S^{-H}B\vec{Y}\|^2$ and that the ML criterion given in (18) corresponds to its optimally weighted LS version. The SNR is defined to be $SNR = 10 \log_{10}(\frac{E_s}{E_n})$, where E_s is the energy of the noiseless received signal $\sum_{l=1}^L \alpha_l p(t - \tau_l)$ and E_n is the variance of the Gaussian noise.

In Fig.2 and Fig.4, we plot the performance of the UWB PQML based algorithm in terms of the NMSE delay estimation. In Fig.3 and Fig.5, we plot the performance of the UWB PQML based algorithm the absolute ranging error versus SNR under different distances. From these figures, it can be seen that the absolute ranging error decreases monotonically as the SNR increases. We also find that the absolute ranging errors of PQML algorithm are significantly smaller than IQML algorithm and the Subspace algorithm. This is due to the PQML algorithm can remove the noise contribution efficiently. The absolute ranging error of PQML algorithm is closed to the absolute ranging error of IQML when the SNR is equal to 30dB. The reason is that the noise is small and hence the second term in (21) is also small at high SNR values.

VII. TEST PQML ALGORITHM UNDER REAL ENVIRONMENTS

Within the Swiss research project on Mobile Information Communication Systems (MICS), an IR UWB testbed has been developed at Ecole Polytechnique Fédérale de Lausanne (EPFL) [40]. Using these facilities, IR UWB measurements campaign was conducted.

In the ranging experiment, the testbed consists of one transmitter, one receiver, one FPGA box and one computer. The transmitter and receiver are connected to the same FPGA board. In Fig.6, the structure of MICS UWB testbed is shown. Fig.7 shows one picture of the testbed.

- 1) On the transmission side, the FPGA is connected to the IR UWB transmitter. The FPGA box generates one signal to trigger one pulse with a center frequency of 4.25GHz and a -10dB bandwidth of 500MHz. The pulse train is transmitted to the receiver. The parameters of the transmitted signals can easily be varied using the FPGA box.
- 2) On the receiver side, the direct-conversion RF receiver is built around a data acquisition board that performs

Fig. 6. The structure of MICS IR UWB testbed.

Fig. 7. MICS IR UWB testbed.

TABLE IV
AVERAGED RANGING ERROR UNDER REAL INDOOR ENVIRONMENTS

Algorithm	Averaged Ranging Error
PQML	1.63cm
IQML	3.17cm
Subspace	8.32cm

sampling at 2GS/s. The sampled signal is fed into the FPGA box where it will be transferred to the computer for off-line processing. The structure of the receiver is shown in Fig.8. The picture of the receiver is shown in Fig.9.

- 3) On the computer side, we use MATLAB to run our PQML based ranging algorithm in order to estimate the distance.

We measure the received signal in the lab. There is a substantial amount electronic equipment in the room. Fig.10 shows the rectangular shape of the room. Fig.7 also shows the propagation environments in the room. Walls around the room are made from heavy cement blocks and there are several steel tubes within the ceiling of the room. The doors are metallic. The antennas of the transmitter and receiver are located about 1m from the floor. To obtain a weak LOS signal, an obstacle (book) was placed between the transmitter and receiver.

About 30 different received signals were measured. The distance between the transmitter and the receiver was about 50cm. Table IV compares the averaged ranging error obtained with the PQML based ranging algorithm, the IQML algorithm and the Subspace one. From this table, it can be seen that the PQML based ranging algorithm outperforms the two other algorithms from a point of view of the obtained ranging error.

VIII. CONCLUSIONS

The developed PQML based ranging algorithm relies on the exploitation of the IR UWB nature of the transmitted signal in combination with an efficient de-noising procedure of the maximum likelihood cost function. This joint combination leads to a good enhancement in the estimation of the ToA of the received IR UWB signal, which translates into reducing

Fig. 8. The structure of MICS IR UWB receiver.

Fig. 9. MICS IR UWB receiver.

the ranging error. Motivated by the good results that we have obtained for the ranging algorithm, we have investigated a related reduced-complexity version of the proposed ranging algorithm that can go for an FPGA implementation. The obtained simulation results have showed that the convergence of the proposed ranging algorithm and also that it significantly outperforms the IQML algorithm and the Subspace one.

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Fig. 10. The shape of the propagation room.

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