MAXIMUM LIKELIHOOD AND ORTHOGONAL SUBSPACE BASED APPROACH FOR IMPROVED IR-UWB CHANNEL ESTIMATION

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ABSTRACT

Indoor propagation channel appears differently to ultra-wideband (UWB) systems than it does to narrowband systems. UWB signals have very high temporal resolution ability and this implies a frequency-selective channel with rich multipath in practice. To capture the signal energy spread over a multipath environment, a Rake receiver consisting of multiple parallel correlators is used. Performance of UWB systems employing Rake receivers is highly dependent on synchronization and the channel estimation. The channel parameters are the attenuations and delays incurred by the UWB signal along the propagation paths. Maximum-Likelihood (ML) and orthogonal subspace (OS) based methods are considered to estimate the parameters for IEEE 802.15.3a standard indoor multipath channel model. Analyzing the limitations and benefits of these methods, a new combined approach is proposed to improve channel parameter estimation.

1. INTRODUCTION

Ultra-wideband technology is becoming a viable solution for short-range high-speed indoor wireless communication. UWB systems are currently being developed to help relieve the spectrum drought caused by an explosion of narrowband systems in the last decade, by offering short-range broadband services using frequencies already allocated to other applications. Impulse based UWB (IR-UWB) is characterized by the transmission of extremely short duration pulses typically on the order of nanosecond to form a communication link [1],[2].

The band allocated by Federal Communication Commission (FCC) for UWB communications is a huge 7.5 GHz band between 3.1 GHz to 10.6 GHz with a transmission power density of – 41.25 dBm/MHz, which helps to minimize the interference on the existing narrowband systems. The use of an extremely huge bandwidth makes it possible to resolve and combine the multipath components (MPCs) at receiver whose path lengths differ by a few tens of centimeters, e.g. 15 cm for a signal bandwidth of 2 GHz. An increase in transmission bandwidth will further improve the capability to resolve the MPCs.

Rake receivers are commonly used to fully exploit the multipath diversity available in UWB systems. In a Rake receiver, each MPC is correlated with a locally generated reference signal and then combined in the end to make the final decision. So, the proper functioning of Rake receiver and eventually the successful operation of UWB system depends critically on the availability of full or partial channel information i.e. information about attenuations and delays incurred by MPCs.

Channel estimation has been studied extensively in the past, mainly for narrowband systems or wideband systems, but there is not as much literature available for UWB channel estimation. In [3],[4] several frequency-domain methods are proposed for UWB channel estimation and rapid acquisition. Both data-aided and non data-aided estimation is presented in [5], based on ML criterion. TOA estimation is focused in [6], also using a ML based approach. OS based methods, are also proposed for channel estimation [7],[8]. However, most of this literature does not take into account the real channel characteristics, some relying on the assumption of non-overlapping MPCs which is not at all valid for UWB channels and others assuming a very small overlapping among MPCs again not valid as the delay among MPCs can be even less than 0.1 ns. The purpose of this paper is to derive channel parameters of real channel model from received waveform. An isolated UWB pulse is transmitted through IEEE 802.15.3a standard channel model and the corresponding received waveform is recorded and analyzed for parameter estimation.

The rest of the paper is organized as follows. Section 2 provides a brief description of IEEE 802.15.3a channel model. Section 3 describes different algorithms for channel estimation along with proposed algorithm. The performance of algorithms is assessed in Section 4. Finally, some conclusions are drawn in Section 5.

2. UWB CHANNEL MODEL

The impulse response of a typical multipath channel is given by:

$$h_{\boldsymbol{\alpha},\boldsymbol{\tau}}(t)=\sum_{l=1}^{L}\alpha_l\delta(t-\tau_l) \qquad (1)$$

where $\boldsymbol{\alpha} = [\alpha_1,\alpha_2,\ldots,\alpha_L]$ and $\boldsymbol{\tau} = [\tau_1,\tau_2,\ldots,\tau_L]$ respectively, are the amplitudes and time delays of L propagation paths.

In this paper, IEEE 802.15.3a standard channel model [9] is used. It is a modified version of Saleh-Velenzuela model, where MPCs arrive in clusters. In this case the channel impulse response (CIR) is mathematically defined as:

$$h(t) = X\sum_{l=1}^{L}\sum_{k=1}^{K}\alpha_{k,l}\delta(t - T_l - \tau_{k,l}) \quad (2)$$

where $\alpha_{k,l}$ is the gain coefficient associated with k^{th} ray of l^{th} cluster, X represents the log normal shadowing, T_l is the delay of l^{th} cluster and $\tau_{k,l}$ is the delay of k^{th} ray within l^{th} cluster relative to the delay of first path of the cluster (T_l).

The cluster and ray arrivals are modeled as Poisson processes with parameters Λ and λ respectively. The amplitudes $\alpha_{k,l}$ of MPCs are log-normally distributed and defined as:

$$\alpha_{k,l} = p_{k,l}\xi_l\beta_{k,l} \quad (3)$$

where $p_{k,l} \in \{-1,+1\}$ is an equiprobable random variable defined for signal inversion due to reflections, ξ_l and $\beta_{k,l}$ are the large-scale and small-scale fading coefficients. Four different measurement environments were defined, namely CM1, CM2, CM3 and CM4. Detailed description of parameters of these models can be found in [9].

The received signal consists of scaled replicas of transmitted UWB pulse $p(t)$ after passing through channel model, which is given by:

$$y(t) = p(t) * h_{\boldsymbol{\alpha},\boldsymbol{\tau}}(t) + \eta(t) = \sum_{l=1}^{L}\alpha_l s(t-\tau_l) + \eta(t) \quad (4)$$

where "*" stands for the convolution product, $s(t)$ is the ideal received UWB pulse with Tx-Rx antenna distortions and $\eta(t)$ is an additive white Gaussian noise (AWGN).

The objective is to estimate the unknown channel parameters $\{\boldsymbol{\alpha}, \boldsymbol{\tau}\}$ using the received signal $y(t)$.

3. UWB CHANNEL ESTIMATION METHODS

The main idea of the algorithm proposed in this paper is to combine ML and OS approaches in order to take advantage of their attractive features and to overcome some of their limitations. So, a brief overview of ML and OS based UWB channel estimation methods is given before proposing our approach.

3.1 ML based UWB channel estimation methods

In the case of Gaussian noise, ML criterion is equivalent to the mean squared error minimization. So the ML estimate of the channel parameters $\boldsymbol{\alpha}$ and $\boldsymbol{\tau}$ are the values which will minimize the following mean squared error:

$$S(\boldsymbol{\alpha},\boldsymbol{\tau}) = \frac{1}{M}\left\|\mathbf{y} - \hat{\mathbf{y}}_{\boldsymbol{\alpha},\boldsymbol{\tau}}\right\|^2 \quad (5)$$

where the vectors $\mathbf{y}$ and $\hat{\mathbf{y}}_{\boldsymbol{\alpha},\boldsymbol{\tau}}$ contain the samples of $y(t)$ and $s(t) * \hat{h}_{\boldsymbol{\alpha},\boldsymbol{\tau}}(t)$ respectively, with $\hat{h}_{\boldsymbol{\alpha},\boldsymbol{\tau}}(t)$ estimated CIR.

The ML estimation used as a basis here is one proposed in [6], namely Search Subtract and Readjust (SSR) algorithm. The idea is simply to calculate the correlation between received signal and reference signal via a matched filter (MF) and finding the largest peak in each iteration, which will correspond to value of τ. The amplitudes $\boldsymbol{\alpha}$ in k^{th} iteration are then calculated by [6]:

$$\begin{bmatrix}\hat{\alpha}_1\\ \vdots \\ \hat{\alpha}_k\end{bmatrix} = \left(\left[\mathbf{s}_1,...,\mathbf{s}_k\right]^T\left[\mathbf{s}_1,...,\mathbf{s}_k\right]\right)^{-1}\left[\mathbf{s}_1,...,\mathbf{s}_k\right]^T\mathbf{y} \quad (6)$$

where $\mathbf{s}_k$ represents the sampled replica of UWB pulse $s(t)$ shifted by delay τ_k. It is clear from above equation that amplitudes are jointly estimated at each step. The estimated paths are subtracted from $\mathbf{y}$ for the next iteration and this process continues until all the paths are estimated.

ML based estimations are relatively simple but may pose some limitations in UWB channels. Mainly, they have limited resolution ability, making them less attractive for UWB channels. Also the estimation degrades significantly for MPCs of small amplitude in the noisy case. One key advantage is that as the algorithm focuses on similarity between received signal and estimated signal, it can provide a low mean-squared error even at low SNR.

3.2 OS based UWB channel estimation methods

These methods, also known as superresolution techniques, are based on the eigenanalysis of the received signal autocorrelation matrix. The observation space is splitted into two orthogonal subspaces called signal subspace and noise subspace. By taking the Fourier transform of $y(t)$ in Eq. (4), we get:

$$Y_s(\nu) = \frac{Y(\nu)}{S(\nu)} = \sum_{l=1}^{L}\alpha_l\exp(-j2\pi\nu\tau_l) + N(\nu) \quad (7)$$

It is clear from above equation that the parameter estimation problem can be seen as a special case of harmonic retrieval problem, which is widely studied in spectral estimation literature [10].

MUSIC and ESPRIT are two familiar methods in this class. They theoretically can provide infinite resolution, but in practice show some limitations. Firstly, the autocorrelation matrix is generally not known, so its estimation is subject to errors. Secondly, as it is parametric approach, precise information about the number of MPCs to be estimated is needed. For this purpose some estimation procedure is used such as Akaike Information Criterion (AIC) or Maximum Description Length (MDL) [11]. Again this estimation is not reliable for low SNR and under-estimation of MPCs present in the received signal may cause errors. These effects become very prominent at low SNR, causing estimation to degrade drastically and making them unsuitable for low SNR scenarios.

3.3 Proposed Algorithm

The block diagram of the proposed algorithm is shown in figure 1, while the description of different steps is given below:

1. Compute the FFT coefficients for the received signal $y(t)$ and the UWB pulse s(t) and form the corresponding vectors $\mathbf{Y}$ and $\mathbf{S}$ respectively. Actually, only the coefficients corresponding to the frequency band of interest (3.1 to 10.6 GHz) are used to further calculate the ratio $\mathbf{Y}_s = \mathbf{Y}/\mathbf{S}$, in order to avoid the risk of dividing by zero.

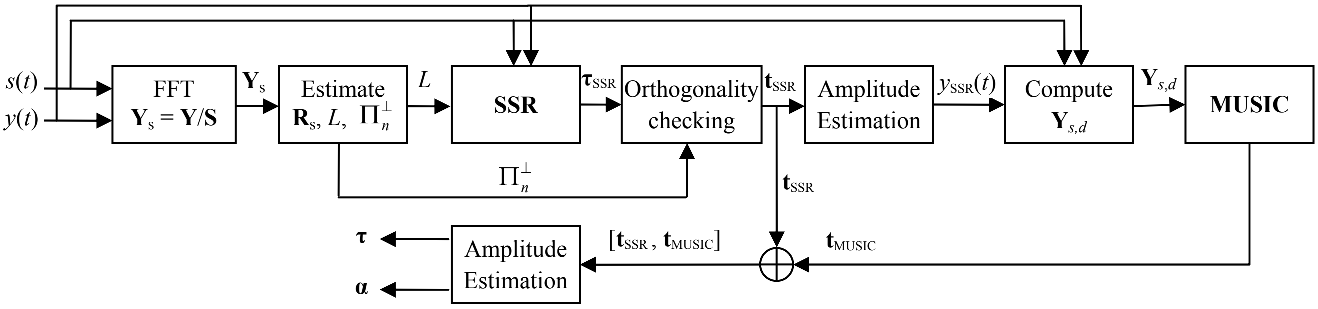

Figure 1 – Block diagram of the proposed algorithm

The Nyquist condition is satisfied here in terms of delays as $1/\Delta f \geq 2\tau_{\max}$, where Δf is the frequency sampling interval and $\tau_{\max}$ is the maximum delay of channel.

2. Form the $p \times q$ data matrix using the $\mathbf{Y}_s$ vector elements:

$$\mathbf{D}_s = \begin{bmatrix} \mathbf{Y}_s(1) & \cdots & \mathbf{Y}_s(q) \\ \vdots & \ddots & \vdots \\ \mathbf{Y}_s(p) & \cdots & \mathbf{Y}_s(N) \end{bmatrix} \tag{8}$$

with $N = p + q - 1$ and $p, q \geq L$.

Next, estimate the data autocorrelation matrix as follows:

$$\hat{\mathbf{R}}_s = q^{-1}\left[\mathbf{D}_s\mathbf{D}_s^H + \mathbf{J}_p\mathbf{D}_s\mathbf{D}_s^H\mathbf{J}_p\right] \tag{9}$$

where $\mathbf{J}_p$ is the $p \times p$ anti-diagonal identity matrix.

The estimate provided by (9) has been preferred to the standard one [12] since it allows improving the Toeplitz structure of the data autocorrelation matrix.

3. Perform the $\hat{\mathbf{R}}_s$ matrix eigenanalysis and obtain the eigenvector matrix $\mathbf{V}$ and the eigenvalue diagonal matrix $\mathbf{\Lambda}$. The eigenvalues are sorted and then used by AIC or MDL criterion to estimate the signal subspace dimension, i.e. the number of MPCs L. The eigenvectors corresponding to the largest L eigenvalues span the signal subspace and form the $\mathbf{V}_s$ matrix. The others span the noise subspace and form the $\mathbf{V}_n$ matrix. The noise subspace projection operator is then calculated as:

$$\Pi_n^{\perp} = \mathbf{V}_n\mathbf{V}_n^H \tag{10}$$

4. Estimate the MPC delays $\boldsymbol{\tau}_{\text{SSR}}=[\tau_1, \tau_2, \dots, \tau_L]$ using SSR algorithm and form the signal vectors:

$$\mathbf{a}_k = \begin{bmatrix} 1 & e^{-j2\pi\upsilon_0\tau_k} & \cdots & e^{-j2\pi(p-1)\upsilon_0\tau_k} \end{bmatrix}^T \tag{11}$$

Validate only the delays resulting in signal vectors orthogonal to the noise subspace, that is:

$$\mathbf{a}_k^H \Pi_n^{\perp} \mathbf{a}_k \cong 0 \tag{12}$$

In the noiseless case false and true peaks are clearly separated. In the noisy case, it is more difficult, but still possible to classify most of them, using some suitable threshold for the projection values. The paths corresponding to projection values above that threshold are considered as false paths and thus eliminated.

5. Use the vector of validated delays, denoted by $\mathbf{t}_{\text{SSR}}$ in figure 1, to estimate the amplitudes of remaining true paths $\mathbf{c}_{\text{SSR}}$ according to (6).

6. Compute the signal $y_{SSR}(t)$ as:

$$y_{SSR}(t) = s(t) * h_{\mathbf{c},\mathbf{t}}^{SSR}(t) \tag{13}$$

Now derive a new observation vector, called difference vector, $\mathbf{Y}_{s,d} = (\mathbf{Y} - \mathbf{Y}_{SSR})/\mathbf{S}$, using only the FFT coefficients in the frequency band of interest, as done in step 1. This newly formed vector will now be used to estimate the remaining paths which were either not estimated at all by SSR or badly estimated and eventually dropped in step 4.

7. Estimate the remaining MPCs from $\mathbf{Y}_{s,d}$ using MUSIC algorithm: follow steps 2 and 3 to estimate autocorrelation matrix and to split observation space into orthogonal signal and noise subspaces, then estimate multipath delays by projecting the vector $\mathbf{a}(\tau) = \begin{bmatrix} 1 & e^{-j2\pi\upsilon_0\tau_k} & \cdots & e^{-j2\pi(p-1)\upsilon_0\tau_k} \end{bmatrix}^T$ onto the noise subspace.

8. The final delays can be given as $\boldsymbol{\tau} = [\mathbf{t}_{SSR}, \mathbf{t}_{MUSIC}]$ while the corresponding amplitudes $\mathbf{c}_{SSR}$ and $\mathbf{c}_{MUSIC}$ are adjusted using (6) to give final coefficients $\boldsymbol{\alpha}$.

4. SIMULATION RESULTS

In this section, performance of different algorithms is analyzed. We have used a specially designed, B-spline based UWB pulse with time duration T_P = 1.28 ns, which fulfills the FCC mask constraints and also optimizes the spectral effectiveness [12],[13]. The channel model used is CM1 which is a line of sight channel with TX-RX (Transmitter-Receiver) distance between 0 to 4 m and is characterized by the impulse response given in figure 2. The strong multipath effect is quite evident from figure 2 as the interval between successive MPCs is much less than T_P.

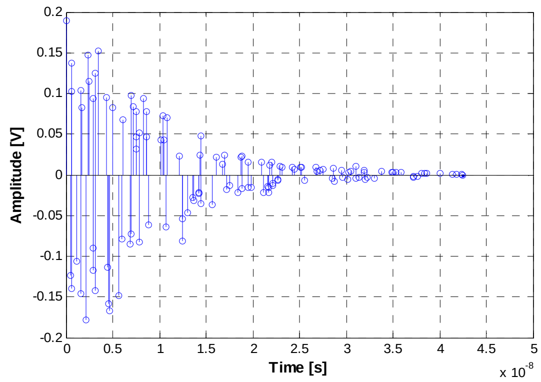

Figure 2 – CM1 channel impulse response

In figure 3, the performance is compared for different algorithms in terms of normalized mean square error, denoted as S_n and given by:

$$S_n(\boldsymbol{\tau},\boldsymbol{\alpha}) = \frac{\left\|\mathbf{y}-\hat{\mathbf{y}}_{\boldsymbol{\alpha},\boldsymbol{\tau}}\right\|^2}{\left\|\mathbf{y}\right\|^2} \qquad (14)$$

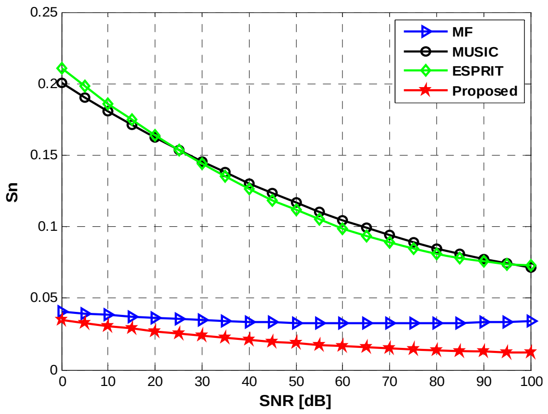

Figure 3 – Normalized mean square error S_n versus SNR in CM1 channel for different algorithms

The estimation is averaged over 500 channels for each value of SNR. The superresolution methods ESPRIT and MUSIC exhibit almost same performance but they do not provide good estimation at low SNRs. The performance for SSR method is same at all SNR values verifying its ability to combat low SNR. The proposed algorithm achieves better performance than others under all SNR values.

The parameter S_n provides good information about matching between received signal and signal reconstructed using estimated channel parameters. However, a low S_n value does not necessarily mean good channel estimation. This phenomenon is depicted in figure 4, where 20 paths of

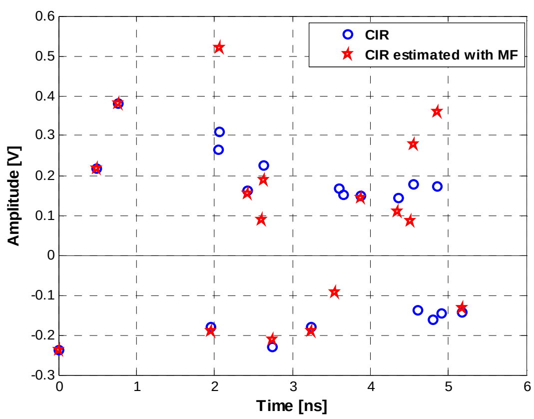

Figure 4 – Estimation of 20 MPCs of CM1 channel with SSR method (SNR=20dB and S_n = 0.0344)

CM1 channel are estimated for SNR = 20 dB with SSR method. It is clear from figure 4 that about half peaks are badly estimated, but yet S_n error is 0.0344 which is excellent. Due to this reason, performance is also assessed in terms of the correlation coefficient between the ideal CIR and the estimated one, denoted by S_{ac} and defined as:

$$S_{ac}(\boldsymbol{\tau},\boldsymbol{\alpha}) = \frac{\left\langle \mathbf{h}, \hat{\mathbf{h}}_{\boldsymbol{\alpha},\boldsymbol{\tau}} \right\rangle}{\left\|\mathbf{h}\right\| \cdot \left\|\hat{\mathbf{h}}_{\boldsymbol{\alpha},\boldsymbol{\tau}}\right\|} \qquad (15)$$

where $\hat{\mathbf{h}}(\boldsymbol{\alpha},\boldsymbol{\tau})$ is the estimated discrete time CIR and < > stands for the scalar product.

S_{ac} value for figure 4 is 0.5955, thus verifying bad estimation. Hence, it is more reasonable to think that a good estimation is one which is good both in terms of S_n and S_{ac}.

The estimation in figure 3 is reproduced in terms of S_{ac} in figure 5.

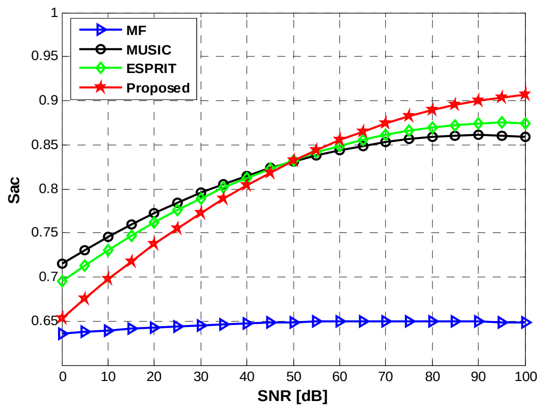

Figure 5 – Correlation coefficient S_{ac} versus SNR in CM1 channel for different algorithms

This figure clearly shows the suboptimal estimation of SSR method. ESPRIT and MUSIC are good in terms of S_{ac} while the proposed algorithm shows an improvement in estimation with increasing SNR, outperforming all methods above 50 dB.

Analyzing results of S_n and S_{ac}, it is quite obvious that at high SNR, proposed algorithm outperforms all others and at low SNR it still provides the best compromise between S_n and S_{ac}.

Finally, Cramer-Rao lower bound (CRLB) is introduced to assess the performance for an academic context with 4 MPCs. The delays of MPCs are defined as τ=[1ns, 1.45ns, 1.5ns, 2ns] while all MPCs have equal amplitudes. As explained in section 3.2 that delay estimation is a special case of harmonic retrieval problem, CRLB for noisy exponentials is taken as a reference given by [14]:

$$\mathrm{var}(\tau_i) \geq \frac{\sigma_n^2 \left[M^{-1}\right]_{ii}}{8\pi^2\alpha_i^2} \qquad (16)$$

where $[\mathbf{M}^{-1}]_{ii}$ is the $[i,i]$ element of the inverse of the $2L\times2L$ Fisher information matrix **M,** with i = 1,3, …, $2L$–1. Figure 6 represents comparison of studied methods with CRLB for 3rd MPC i.e. MPC with delay 1.5ns, as it is most severely affected by other MPCs. Clearly, SSR is suboptimal as it can not differentiate two peaks as close as 0.05ns. ESPRIT turns out a better estimator in this case while our method also showing a performance very close to ESPRIT. However, it has been observed that OS based methods are also sensitive to the number of multipaths to be estimated.

So, the performance of those methods is not same for 100 MPCs and for 4 MPCs. This fact is already visible from figure 3 where MPCs may reach up to 100 and in that case the performance of OS does not remain as optimal as suggested in figure 6 for 4 MPCs, where our algorithm still remains acceptable in both cases.

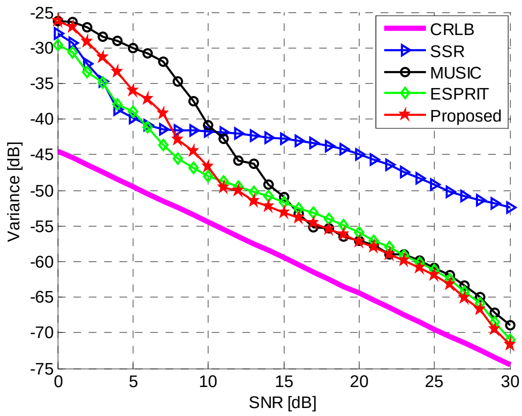

Figure 6 – CRLB and variance of different methods vs SNR

5. CONCLUSION AND FUTURE WORK

Channel estimation is a key point for any communication system and even more for a IR-UWB because of the dense multipath associated environment. ML estimators, which are implemented through MF, have been generally used so far, since they show robustness to noise. However, they have limited resolution and are not able to resolve very close multipaths. This may become a critical point if the amplitudes of the unresolved multipath is higher enough to be taken into account by the S-Rake receiver for example. Time domain superresolution methods could be an interesting solution from this point of view, but they are too sensitive to noise. The method proposed in this paper combines the advantages of the two approaches and removes their drawbacks. An ML estimator is used in the first stage, thus taking advantage of its robustness to noise. The provided solution is then validated using noise subspace projection operator and only the peaks satisfying the orthogonality constraint are conserved. A superresolution method is finally used to resolve the remaining peaks given the partial solution obtained previously. The proposed algorithm is compared to several reference methods and its performance is assessed in the framework of a real UWB channel model. It is shown that the new method can cope with noisy UWB channels and provides best performance in both low and high SNR scenarios. Its main limitation is the increased processing complexity due essentially to the eigenanalysis required by the superresolution stage. Finding solutions to reduce this additional complexity is the first objective of our future work. The second one is to imagine new Rake receiver structures being able to better exploit the additional information in terms of resolution, provided by the proposed channel estimation method.

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