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إعتماد فلتر كالمان عديم الإشتقاق لقياس إستجابة القنوات وتصنيف إحتوائها على مسارات مباشرة وغير مباشرة في شبكات الإتصالات اللاسلكية ذات النطاق العريض

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الخلاصة

يدرس هذا البحث تقدير وقياس إستجابة قنوات الإتصالات اللاسلكية ذات النطاق العريض وحالات وجود المسارات المباشرة وغير المباشرة وذلك بإستعمال فلتر كالمان عديم الإشتقاق وتحليل خصائص إستجابة القناة.

يعتبر فلتر كالمان عديم الإشتقاق ناجعا في التقديرات القائمة على الخطأ المربع الأدنى بالنسبة للأنظمة الغير خطية، وقد وقع إستعماله في هذا البحث لقياس إستجابة قنوات الإتصالات ذات النطاق العريض كما أثبتت النتائج العددية كفاءته في تقديرقوة وتأخير قنوات الإتصالات اللاسلكية ذات النطاق العريض .

في مرحلة ثانية وقع إستخراج خصائص إحصائية للقنوات تتعلق بالتفرطح ومتوسط التأخير الزائد بإستعمال عدد محدود من أصداء إستجابة القناة. وقد تبين وجود فروقات واضحة بين خصائص القنوات تبعا لوجود مسارات إنتشار مباشرة أو غير مباشرة بالنسبة لبيئات مختلفة تشتمل على محلات سكنية ومكاتب وأماكن مفتوحة ومناطق صناعية. كما وقع إستعمال دالات الكثافة الإحتمالية لهاته الخصائص للقيام بإختبارات أرجحية لتصنيف القنوات المختلفة من حيث إشتمالها على مسارات إنتشار مباشرة أو غير مباشرة. و قد أثبتت النتائج الرقمية المقدمة مدى نجاعة هذا التصنيف الذي تجاوزت نسبة دقته 90% في مجمل الحالات ذات الأهمية العملية، مما يفسح المجال لتطبيقه في وقت لاحق لتحسين أداء نظم تحديد المواقع المعتمدة على الإشارات اللاسلكية ذات النطاق العريض.

UKF-based channel estimation and LOS/NLOS classification in UWB wireless networks

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ABSTRACT

The paper addresses Ultra-wideband (UWB) channel estimation and line-of-sight (LOS) vs. non-line of sight (NLOS) classification based on the application of the Unscented Kalman Filter (UKF) and the analysis of multipath channel response characteristics. For non-linear models, the UKF provides an efficient recursive minimum mean squared error estimation technique that is successfully applied in this work, and supported by numerical results demonstrating its effectiveness in UWB multipath channel gain and time delay estimation. The multipath channel response obtained from a limited number of channel taps is subsequently characterized in terms of relevant statistical parameters including Kurtosis and Mean Excess Delay. This characterization reveals clear differences in the statistics of these parameters under LOS and NLOS propagation conditions for various channel types including residential, office, outdoor and industrial environments. Based on the estimated parameters' probability density function (PDF) under LOS/NLOS hypotheses, a likelihood ratio test (LRT) for hypothesis classification is performed for the different UWB channel models. Numerical results show that highly reliable LOS vs. NLOS classification is achievable with accuracy exceeding 90% for most cases of practical interest, which can then be further exploited in enhancing the performance of UWB-based positioning applications.

Keywords: Channel estimation; LOS/NLOS classification; unscented Kalman filter; UWB.

INTRODUCTION

Accurate estimation of the multipath channel profile is important for wireless communication system design and performance analysis. Channel estimation is not only critical for optimum data detection, but is equally important for other applications such as positioning and radiolocation in wireless sensor networks (WSN) and mobile cellular systems. In this paper, we focus on multipath channel tap delay and amplitude profile estimation in ultra-wideband (UWB) wireless sensor networks, which are finding increased interest in a wide array of applications (Benedetto *et al*., 2006; Sahinoglu *et al*., 2008). UWB schemes employ broadband, impulse-like high-resolution signaling waveforms, which offer many advantages for high accuracy ranging and localization, but also pose challenges for signal delay and amplitude estimation. It is known that Kalman filtering (KF) techniques use dynamic state space models to obtain recursive solutions to optimal minimum mean square error (MMSE) filtering problems without the need for storing the entire past observed data, thereby providing computationally efficient means for finding optimal estimates at each step of the filtering process (Wan & Merwe, 2001). In the context of wireless multipath channel estimation, KF techniques use state and observation models representing the channel amplitudes and delays, and have the advantage of tracking time-changing multipath profiles. In previous works, KF channel estimation techniques have efficiently been applied to delay estimation, especially when closely-spaced multipath echoes are present. For example, KF-based algorithms have been used in direct-sequence (DS) spread-spectrum code delay estimation with sub-chip spaced paths (Caffery & Stuber, 2000; Kim & Iltis 2002; Lakhzouri *et al*., 2003). For UWB systems, different channel estimation approaches for data detection purposes have been proposed in Cheng *et al*. (2012); Fang *et al*. (2012); Cheng *et al*. (2010); Chen & Beaulieu (2010); Thomas *et al*. (2010); Sato & Ohtsuki (2006). In particular, the application of KF methods to DS-type and orthogonal frequency division multiplexing (OFDM) UWB was also discussed in Islam & Kwak (2010); Zhiyuan *et al*. (2009); Sethi *et al*. (2006). However, it is noted that many of these works assume a linearized system model, and adopt the extended Kalman filter (EKF), which relies on simplifying assumptions that can introduce errors. In our case, we consider the use of the unscented Kalman filter (UKF), a newly introduced structure by Julier & Uhlmann (2004) which is particularly well-suited for estimation models with nonlinearities (e.g., for timing delays), and is also robust in the presence of dense multipath propagation with closely-spaced signal epochs commonly encountered in UWB signaling. Unlike the EKF approach, which uses linearization to obtain a first-order Taylor series truncation of the system representation, the UKF utilizes the "full" nonlinear system model, and the state distribution is estimated with low complexity using a minimal set of selected sample points as will be discussed shortly. A comparison of the UKF, EKF and other related methods can be found in Khan *et al*. (2009). It is also noted that UKF-based channel estimation and iterative decoding was applied by Kang & Ilti (2007) to OFDM schemes, and by Meng *et al*. (2013) to 2D-spread WCDMA. It has been recently adopted to relay networks in Zhang *et al*. (2014) and Li & Xia (2013) as well.

In this work, we develop and implement a system model for UKF-based discrete channel tap amplitude and delay estimation, and demonstrate its effectiveness with UWB signaling in Nakagami wireless multipath fading environments. This is then used in a second part of the paper where the important issue of channel type classification in terms of line-of-sight (LOS) versus non-line-of-sight (NLOS) propagation is addressed based on the multipath channel profile. This classification is useful for aiding radiolocation algorithms in the mitigation of NLOS-biased measurements and improving ranging accuracy (Guvenc *et al*., 2008; Mucchi & Marcocci, 2009; Marano *et al*., 2010; Muqaibel *et al*., 2013). It is indeed possible to exploit certain statistical parameters derived from the channel response amplitude and delay information to determine the channel type (Shen *et al*., 2010; Yanjia & Law, 2012;Ying *et al*., 2012). In particular, the channel response kurtosis, mean excess delay and root mean square delay statistics can effectively be used for LOS/NLOS classification. In Guvenc *et al*. (2008), this was done assuming the "full" multipath profile (which includes a very large number of echoes) is readily available. However, this would not be easily feasible in practice. Instead, we take a more practical approach with a two-step procedure that can be applied in real-time to continuously monitor LOS/NLOS links. First, a UKF-based procedure is applied to estimate and track a number of dominant multipath taps. Then, using the known statistics of key parameters (kurtosis and mean-excess delay), a likelihood ratio test is performed in a second stage to decide on LOS/NLOS classification. This approach will be implemented and tested to demonstrate its viability for a variety of UWB channel models pertaining to different user environments.

The rest of the paper is organized as follows. In Section 2, the UKF framework is developed and applied to channel amplitude and delay estimation. In Section 3, the multipath channel response characterization and its various parameters are presented. In Section 4, LOS/NLOS classification for various channel profiles is discussed, and numerical results based on likelihood ratio tests are presented to quantify the viability of the proposed techniques. Final conclusions are then summarized in Section 5.

UKF-BASED UWB CHANNEL ESTIMATION

System model

We consider a discrete-time multi-tap channel UWB model commonly used for wireless propagation scenarios. At the l-th sampling instant lT_s (where the sampling period is T_s), the received multipath channel output can be represented by:

$$y(l) = \sum_{i=1}^{M} c_i\,(l)p[lT_s - \tau_i(l)] + n(l) \quad (1)$$

where M is the number of resolvable channel multipaths, $c_i(l)$ and $\tau_i(l)$ are the fading channel tap amplitude and time delay of the i^{th} path, $p(l)$ is the impulse-like UWB signal sample, and $n(l)$ represents additive white Gaussian noise (AWGN). Without loss of generality, the dependence on transmitted data symbols has been omitted (as with a deterministic pilot sequence) in order to simplify the model. It is also noted that the representation takes into account small-scale multipath fading modeled by Nakagami distributions commonly encountered for UWB channels with discrete path delay profiles (Simon & Alouini, 2005; Molish *et al.*, 2006). Other models may encompass shadowing and pathloss effects, but these are not relevant to the small-scale average channel response amplitude and delay estimation being pursued in this work.

As discussed in the introduction, the UKF framework is well-suited for the problem at hand and will be adopted for channel tap gains and delays estimation and tracking. To this end, a state-space representation is used, whereby the M-tap channel has $2M$ unknown parameters (multipath amplitudes and delays) to be estimated are represented by a $2M$-long vector:

$$\boldsymbol{x} = [\boldsymbol{c}\ ;\ \boldsymbol{\tau}] \tag{5}$$

where $\boldsymbol{c}= [c_1, c_2, c_{3\ldots}c_M]^{\mathrm{T}}$, and $\boldsymbol{\tau}= [\tau_1, \tau_2, \tau_{3\ldots}\tau_M]^{\mathrm{T}}$ denote the amplitudes and delays, respectively. For a time-varying system, the unknown channel parameters (state vector) is assumed to obey a Gauss-Markov dynamic channel model given by:

$$\boldsymbol{c}\,(l+1) \ = \ \boldsymbol{F}_c\boldsymbol{c}(l) \ + \ \boldsymbol{v}_c(l) \tag{6}$$

$$\boldsymbol{\tau}\,(l+1) \ = \boldsymbol{F}_\tau\,\boldsymbol{\tau}(l) \ + \ \boldsymbol{v}_\tau(l) \tag{7}$$

where $\boldsymbol{F}_c$ & $\boldsymbol{F}_\tau$ are M-by-M state transition matrices, and $\boldsymbol{v}_c(l)$ and $\boldsymbol{v}_\tau(l)$ are M-long mutually independent zero-mean Gaussian random vectors. Hence, the state model can be rewritten as:

$$\boldsymbol{x}(l+1) \ = \begin{bmatrix}\boldsymbol{F}_c & 0\\ 0 & \boldsymbol{F}_\tau\end{bmatrix}\boldsymbol{x}(l) + \boldsymbol{v}(l) \tag{8}$$

where $\boldsymbol{F}=\begin{bmatrix}\boldsymbol{F}_c & 0\\ 0 & \boldsymbol{F}_\tau\end{bmatrix}$ is a $2M$-by-$2M$ state transition matrix and $\boldsymbol{v}(l) = [\boldsymbol{v_c}(l)\ \boldsymbol{v_\tau}(l)]^T$ is a $2M$-long noise vector. On the other hand, from Eq.(1) the system output measurement is expressed in terms of the state vector $\boldsymbol{x}(l)$ as follows:

$$y(l) = h\big(\boldsymbol{x}(l)\big) + n(l) \tag{9}$$

and it is seen that $h(.)$ is a nonlinear transformation of the state $\boldsymbol{x}(l)$ because of its dependency on the multipath delays, as shown in Equation (1). The optimal estimation of $\boldsymbol{x}(l)$ using the state-space dynamic Gauss-Markov model can be addressed by means of the UKF filter presented next. The UKF is applied to the nonlinear system model to recursively achieve optimum estimation of the channel response.

The UKF Algorithm

The UKF algorithm was introduced by Julier & Uhlmann (2004) and uses a nonlinear transformation known as the unscented transformation (UT) in which a given state probability distribution is represented by a minimal set of sampled points that can be used to parameterize the true mean and covariance of the state distribution. The UT provides a method for obtaining the statistics of a random variable (or vector) that undergoes a nonlinear transformation, and can capture the mean and covariance information, while allowing the direct propagation of the data through the nonlinear transformation. This is achieved by using a minimum set of "sigma" (sample) points, where each point is directly transformed by the nonlinear mapping. For a given Gaussian-distributed vector with a given mean and covariance, the state distribution is defined using the set of selected sigma points to completely capture the true mean and covariance of the Gaussian vector, and when propagated through the nonlinear system, this will also represent the posterior mean and covariance accurately up to the 2nd order for any nonlinearity.

For the unknown state '$\boldsymbol{X}_i$' assumed to have n-dimensional Gaussian distribution with a given mean $\overline{\boldsymbol{x}}$ and covariance $\boldsymbol{P}$, the set of $2n$ sigma points are given, as noted in Julier & Uhlmann (2004), by:

$$\boldsymbol{X}_i = \overline{\boldsymbol{x}}, \quad i=0 \tag{10}$$

$$\boldsymbol{X}_i = \overline{\boldsymbol{x}} + [\{(n+\lambda)\boldsymbol{P} + \boldsymbol{Q}\}^{1/2}]_i\,, \; i = 1, \ldots, n \tag{11}$$

$$\boldsymbol{X}_i = \overline{\boldsymbol{x}} - [\{(n+\lambda)\boldsymbol{P} + \boldsymbol{Q}\}^{1/2}]_{i-n}\,, \; i = n+1, \ldots, 2n \tag{12}$$

with $[\;]_i$ denoting the i-th column vector, $n + \lambda = \alpha^2(n+k)$ is a scaling parameter, α can be used to control the spread of the sigma points, k is a parameter used to describe the scaling direction, and $\boldsymbol{Q}$ is the covariance of the noise process. Sigma points are translated using the unscented transformation where the sigma points for $\boldsymbol{x}$ are first evaluated using Equations (10)-(12), and transformed to a new set of points for $\boldsymbol{y}$ by means of the nonlinear mapping. The new sigma points are then used to evaluate the posterior mean and posterior covariance of $\boldsymbol{y}$.

The formulation of the UKF algorithm is as follows. First, the state prediction is performed using:

$$\boldsymbol{X}_i(l+1|l) = \boldsymbol{F}\boldsymbol{X}_i(l|l) \tag{13}$$

Next, the predicted state vector mean and covariance matrix are computed as:

$$\hat{\boldsymbol{x}}(l+1|l) = \sum_{i=0}^{4M} W_i^{(m)} \boldsymbol{X}_i(l+1|l) \tag{14}$$

$$\boldsymbol{P}(l+1|l) = \sum_{i=0}^{4M} W_i^{(c)} [\boldsymbol{X}_i(l+1|l) - \hat{\boldsymbol{x}}(l+1|l)][\boldsymbol{X}(l+1|l) - \hat{\boldsymbol{x}}(l+1|l)]^T \tag{15}$$

where the weights can be chosen as:

$$W_i^{(m)} = \begin{cases} \frac{\lambda}{\mathrm{n}+\lambda} & i=0 \\ \frac{1}{2(n+\lambda)} & i=1,\ldots.2n \end{cases} \tag{16}$$

$$W_i^{(c)} = \begin{cases} \frac{\lambda}{\mathrm{n}+\lambda} + (1-\alpha^2+\beta) & i=0 \\ \frac{1}{2(n+\lambda)} & i=1,\ldots.2n \end{cases} \tag{17}$$

where the parameter α controlling the sigma points spread can be set between 0 and 1 ($0 \leq \alpha \leq 1$), and the parameter β may add prior knowledge about the distribution of $\boldsymbol{x}$. Based on the nonlinear transformation $h(.)$, the propagated sigma points are updated through:

$$\boldsymbol{Y}_i(l+1|l) = h(\boldsymbol{X}_i(l+1|l)) \tag{18}$$

The predicted observation mean and posterior covariance are computed as:

$$\hat{\boldsymbol{y}}(l+1|l) = \sum_{i=0}^{4M} W_i^{(m)} \boldsymbol{Y}_i(l+1|l) \tag{19}$$

$$\boldsymbol{P}_{yy}(l+1) = \sum_{i=0}^{4M} W_i^{(c)} [\boldsymbol{Y}_i(l+1|l) - \hat{\boldsymbol{y}}(l+1|l)][\boldsymbol{Y}_i(l+1|l) - \hat{\boldsymbol{y}}(l+1|l)]^T \tag{20}$$

The innovation covariance is obtained as:

$$\boldsymbol{P}_{vv}(l+1) = \boldsymbol{P}_{yy}(l+1) + \sigma_n^2 \tag{21}$$

where σ_n^2 is the noise variance. On the other hand, the cross-covariance of $\boldsymbol{x}$ and $\boldsymbol{y}$ is obtained from:

$$\boldsymbol{P}_{xy}(\mathrm{l}+1) = \sum_{i=0}^{4M} W_i^{(c)} [\boldsymbol{X}_i(l+1|l) - \hat{\boldsymbol{x}}(l+1|l)][\boldsymbol{Y}_i(l+1|l) - \hat{\boldsymbol{y}}(l+1|l)]^T \tag{22}$$

and the Kalman gain is calculated as:

$$K(l+1) = \boldsymbol{P}_{xy}(l+1)(\boldsymbol{P}_{vv}(l+1)) - 1 \tag{23}$$

Finally, the updated mean state estimate is obtained as:

$$\hat{\boldsymbol{x}}(l+1) = \hat{\boldsymbol{x}}(l+1|l) + K(l+1)\boldsymbol{v}(l+1) \tag{24}$$

where $\boldsymbol{v}(l+1)$ is the innovation component given by:

$$\boldsymbol{v}(l+1) = \boldsymbol{y}(l+1) - \hat{\boldsymbol{y}}(l+1|l) \tag{25}$$

and the updated covariance is:

$$\boldsymbol{P}(l+1) = \boldsymbol{P}(l+1|l) - K(l+1)\boldsymbol{P}_{yy}(l+1)K^T(l+1) \tag{26}$$

Channel estimation results

The UKF processing steps described above have been implemented in numerical simulations to demonstrate the efficiency of the UKF in both estimating and tracking the tap amplitudes and delays for channels with Nakagami-fading path gains and decaying average power delay profiles. DS-UWB signals are assumed with 32 bit-long frames, spreading sequence of length 16 chips per bit, and a sampling rate of 16 samples per chip is used. In the subsequent results, a 10dB average SNR is assumed, and the impulse-like waveform is based on the 2nd derivative of the Gaussian monocycle pulse widely adopted in UWB and given by $p(t) = A(1 - 4\pi t^2/\varepsilon^2)\exp(-2\pi t^2/\varepsilon^2)$, where A and ε are parameters chosen to have normalized unit energy and pulse duration (set to T_c=1ns). The path delays are assumed slowly varying, with constant values over each bit period, but the path gains are assumed to change at faster pace for each chip. Fractional-chip spacing of the path delays is also assumed. Simulations were run for various values of the Nakagami parameter μ, but for space limitation results are only reported for the case μ=1 as other values led to similar observations (Mahmoud, 2011). A number of $2M$ positive and negative sigma points are used for the UKF algorithm. The parameters α and β are set to one and zero, respectively. For algorithm initialization, delay errors to within half a chip, and initial amplitude errors of 50% were used. The state space model is assumed to use a transition matrix $\boldsymbol{F}=0.999\boldsymbol{I}_{n\times n}$ and process noise covariance matrix $\boldsymbol{Q}=0.001\boldsymbol{I}_{n\times n}$.

The UWB multipath profile estimation results are illustrated in Figures 1 and 2. First, in Figure 1, channel tap delay estimation and tracking capability is demonstrated for a 4-tap channel, where it is observed that the UKF estimates converge to the actual delays, and can track newly changing values quite accurately.

Likewise, in Figure 2, channel amplitude estimates for the 4 paths are shown, and it is again seen that the UKF is able to reliably estimate and track the channel tap amplitudes. It should be noted that the convergence in this case is faster than for the delays, because the system model is linear in terms of the amplitudes and non-linear vis-à-vis the delays. It was also found that accurate UKF-based channel amplitude and delay estimation capability is achievable with an increased number of paths as well. However, this is at the expense of a higher computational load and increased number of iterations.

In summary, the UKF viability for obtaining the UWB multipath channel response is clearly established, and the channel profile characteristics will be used next for subsequent LOS/NLOS classification.

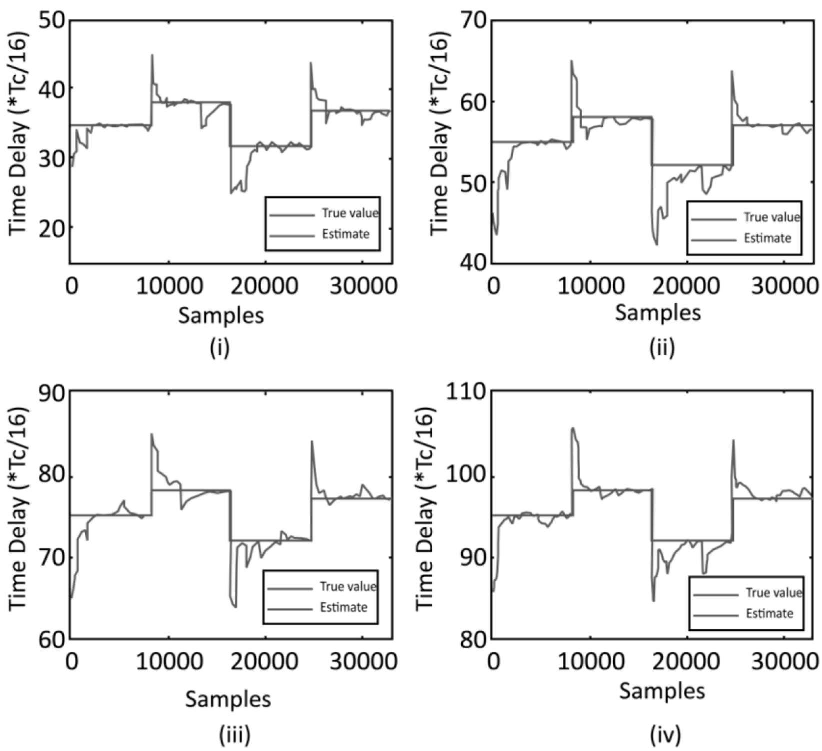

Fig. 1. UKF tap delay estimation for 4 paths, (i) through (iv).

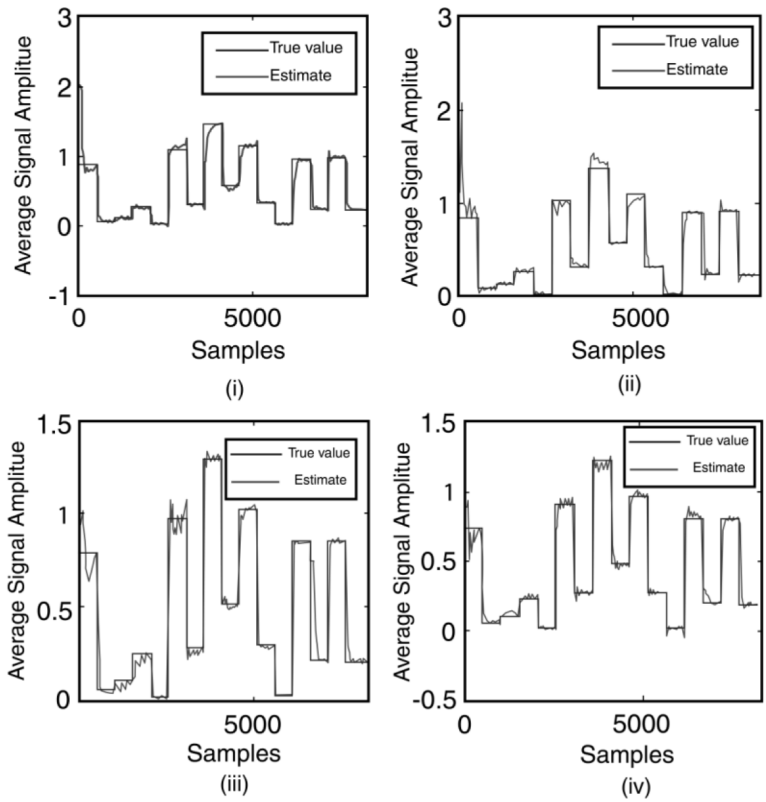

Fig. 2. UKF tap gain estimation for 4 paths, (i) through (iv).

UWB CHANNEL CLASSIFICATION

Classification parameters

There are several important parameters that can be extracted from the multipath channel response and used for the characterization of the type (LOS or NLOS) of propagation environment. This is particularly useful in positioning applications with UWB signals, where NLOS identification is crucial since the NLOS paths introduce strong bias in the time-of-arrival ranging measurements used in position determination. The relevant parameters needed for this classification are related to either amplitude information, e.g., channel response kurtosis (K), or delay information as with mean excess delay (MED). Other parameters may also be considered, but in this work we find that the use of K and MED provides a reliable means for proper channel identification, as will be shown subsequently. In Guvenc *et al*. (2008), these parameters have also been used for channel classification, but the results were based on simulated IEEE 802.15.4a UWB channel response profiles, which include hundreds of multipath echoes (Molish *et al* ., 2006). However, in this paper, we emphasize that only a limited number of multipath channel taps can be practically estimated in actual UWB receiver operation (by means of the UKF, as suggested in this work, or by any other estimation technique), since it is not feasible to estimate a very large number of paths with acceptable processing complexity. As will be shown next, with a reasonable number of 10 to 20 dominant paths for the estimated channel profiles, it is possible to achieve highly reliable UWB LOS/NLOS channel type identification results.

Going back to the key channel characteristics that will be employed for classification, first we have kurtosis which is defined as the ratio of the fourth central moment of the data to the square of the second central moment; this gives the following expression for given a channel response *h(t)*:

$$K = \frac{E[(|h(t)| - \mu_{|h|})^4]}{E^2[(|h(t)| - \mu_{|h|})^2]} \tag{27}$$

where $\mu_{|h|}$ is the mean of the magnitude of *h(t)*. Kurtosis is related to the flatness of the data (relative to a normal distribution). Data with high kurtosis tend to have a distinct peak near the mean and decline rapidly with heavy tails, while data with low kurtosis has a flat top around the mean. As noted, while kurtosis provides information about the amplitude distribution of the channel response, it does not provide information regarding the delay spread properties. This information may be captured by other parameters such as the mean excess delay, which gives an indication of the time spread of the channel response, and is defined by:

$$\tau_{med} = \frac{\int_0^\infty t|h(t)|^2 dt}{\int_0^\infty |h(t)|^2 dt} \tag{28}$$

Other parameters could be used as well (Guvenc *et al.*, 2008). However, we find that that the kurtosis and mean excess delay measures are sufficient. For the UWB-based wireless sensor networks being considered, the classification will be based on eight types of channel profiles defined by the IEEE 802.15.4a channel models (Molish *et al.*, 2006) and designated by CM1 through 8, where the odd (CM1, CM3, CM5, and CM7) represent LOS scenarios, and the even (CM2, CM4, CM6 and CM8) are NLOS ones. More specifically, CM1 & CM2 are for residential indoors, CM3 & CM4 correspond to office environments, CM5 & CM6 apply to outdoor environments; and CM7 & CM8 are for industrial sites.

Statistics of the classification parameters

For the purpose of illustrating the usefulness of kurtosis and MED parameters for channel identification, the probability density function (PDF) for both LOS/NLOS channels (in a given environment) were obtained by normalized histograms with up to

1000 realizations of channel responses, and twenty paths were used in generating the PDF plots. From the results, it can be observed that the statistics of K and MED vary considerably depending on whether the link is LOS or NLOS. This is clearly seen in Figure 3, which shows that CM1-CM2, CM3-CM4 and CM7-CM8 have very distinct ranges for kurtosis, although the distinction becomes less sharp for CM5-CM6 (but still informative). Likewise, in Figure 4, clear differences in MED are observed in CM3-CM4, CM5-CM6 and CM7-CM8, but the distinction is more blurred for CM1-CM2. These observations suggest that both parameters should be taken into account to yield a more reliable classification. The next section discusses a likelihood ratio test that can be implemented to perform systematic LOS/NLOS channel classification.

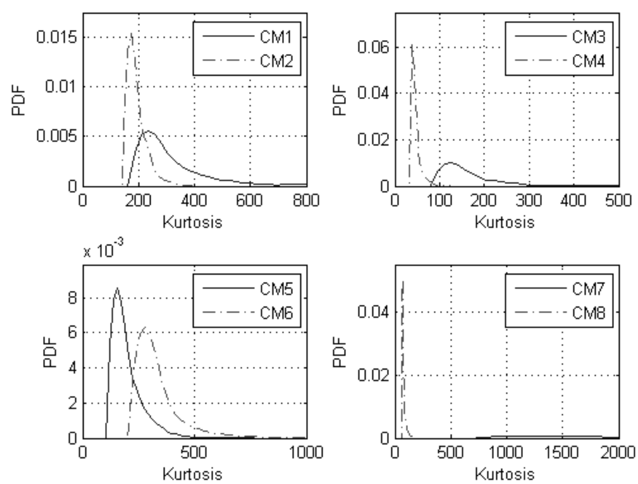

Fig. 3. Kurtosis PDFs for different UWB channel types.

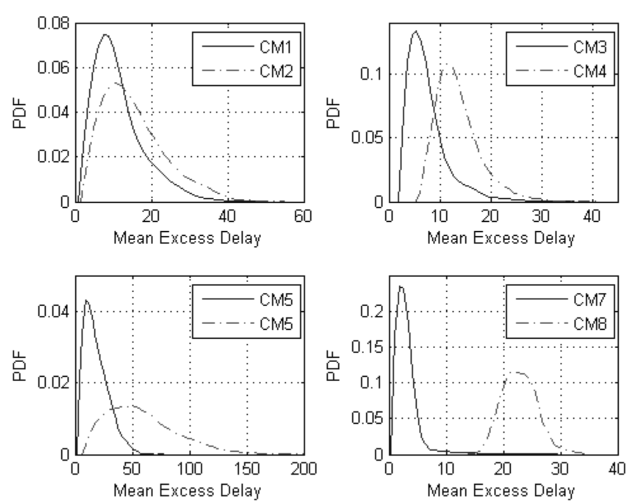

Fig. 4. Mean excess delay PDFs for different UWB channel types.

LOS/NLOS LIKELIHOOD CLASSIFICATION

Likelihood ratio test

Once the multipath channel taps are estimated, it is possible to obtain reliable LOS/NLOS classification by exploiting the statistical differences in channel response parameters (K and MED) described previously. To this end, the problem may be formulated as a binary hypothesis testing, where a likelihood ratio test (LRT) can be applied as suggested in Guvenc *et al*. (2008). However, as noted above, only a subset of the dense channel response may be estimated in a practical reduced-complexity implementation. Therefore, we use selected paths corresponding to the peaks of the multipath channel profile that are easily tracked by means of the UKF, as discussed in Section 2.

The PDFs of the channel response kurtosis K and mean excess delay MED can be used to perform LRT under LOS and NLOS hypotheses for any pair of environments (CM1-CM2 to CM7-CM8). The PDFs of these parameters are first stored (offline) based on histograms built with multiple channel realizations under both LOS and NLOS assumptions, and for a given channel response realization with unknown type (but know environment, e.g., office, outdoors, etc.), the following LRT tests can be performed with minimal complexity to test the LOS and NLOS hypotheses. If the LRT is larger than 1, the LOS hypothesis (H_0) is chosen. Otherwise, NLOS hypothesis (H_1) is selected instead:

$$\frac{P_K^{(LOS)}(k)}{P_K^{(NLOS)}(k)} \underset{H_1}{\overset{H_0}{\gtrless}} 1 \tag{29}$$

$$\frac{P_{MED}^{(LOS)}(\tau_{med})}{P_{MED}^{(NLOS)}(\tau_{med})} \underset{H_1}{\overset{H_0}{\gtrless}} 1 \tag{30}$$

It is possible to further simplify the LRT by using a single threshold comparison, as can be seen from the PDF plots. For instance, with CM1 and CM2 channels, a kurtosis threshold around 220 may be used to distinguish LOS from NLOS links. For CM3-CM4, the threshold is around 80. Likewise, for MED, a threshold of 12 is applicable for CM1-CM2, and so on. Using the LRT approach, numerical results that illustrate the accuracy of channel type identification are presented next.

Numerical classification results

For each of the UWB eight channel profiles, likelihood ratio test results are obtained based on extensive simulation runs with up to 1000 channel realizations to check the reliability of identification for each channel model. The percentage of correct channel identification is computed and results are tabulated in Table 1 for LOS and Table for NLOS. As can be seen from the data, kurtosis proves to be quite reliable in general for identifying true LOS or NLOS channels. Except for CM5, the percentage of correct identification exceeds 85% for all other scenarios (and 90% for most cases). For CM5, it is seen from Figure 4 that the large overlap in the PDF's is the main reason for the reduced identification accuracy. On the other hand, with mean excess delay, the identification accuracy is generally less than kurtosis, especially for CM1-CM2, which is attributed to the largely overlapping PDFs in Figure 5(a). However, it is found to be better for CM5 in particular, which suggests that both parameters should be used together to complement each for more reliable classification. It is also noted that in outdoor/industrial environments, the statistics of the different parameters are clearly distinct, and nearly perfect identification is always achievable. This is quite useful as many sensor positioning applications would be in such environments.

In summary, it is therefore observed that the joint use of kurtosis and mean excess delay can provide very reliable LOS/NLOS classification for different types of UWB WSN environments.

Table 1. LRT-based correct channel identification rates for LOS channels in different environments.

Parameters / LOS Channel	Kurtosis	MED
CM1 (Residential)	92.1%	66.2%
CM3 (Office)	96.4%	74.4%
CM5 (Outdoor)	79.5%	91.3%
CM7 (Industrial)	99.9%	97.5%

Table 2. LRT-based correct channel identification rates for NLOS channels in various environments.

Parameters / NLOS Channel	Kurtosis	MED
CM2 (Residential)	84.1%	56.2%
CM4 (Office)	98.7%	91.1%
CM6 (Outdoor)	92.5%	76.8%
CM8 (Industrial)	100%	98.7%

CONCLUSION

This paper presented an efficient approach for UWB wireless channel estimation based on the application of the unscented Kalman filter, which is well-suited for nonlinear system models. A problem formulation for multipath channel tap amplitude and delay estimation was developed and a UKF-based optimal recursive estimation technique was derived, with numerical simulation results showing that the channel tap gains and time delays can be accurately estimated and tracked by means of the UKF. In a second part, the paper presented key statistical parameters that characterize the multipath channel response and its dependency on line-of-sight versus non-line-of-sight propagation conditions. Kurtosis and mean-excess delay probability density functions were used to show that LOS/NLOS distinction is achievable by estimating a limited number of channel taps which can be easily achieved by the UKF. The reliability of channel of true channel type identification was demonstrated by numerical simulations using UWB standard channel models covering residential, indoor, outdoor, and industrial settings. A likelihood ratio test for LOS/NLOS hypothesis testing was used and numerical results showed that correct channel type identification accuracy levels exceeding 90% are achievable for all practical purposes. With reliable LOS/NLOS channel classification, future applications of this work may be envisioned in addressing the problem of NLOS bias mitigation in UWB positioning applications.

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