Journal of the Korean Institute of Illuminating and Electrical Installation Engineers Vol. 21, No.4, pp. 96~103 May 2007 논문 21-4-12

A Study on High Resolution Ranging Algorithm for The UWB Indoor Channel

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Abstract

In this paper, we present a novel and numerically efficient algorithm for high resolution TOA(Time Of Arrival) estimation under indoor radio propagation channels. The proposed algorithm is not dependent on the structure of receivers, i.e, it can be used with either coherent or non-coherent receivers. The TOA estimation algorithm is based on a high resolution frequency estimation algorithm of Minimum-norm. The efficiency of the proposed algorithm relies on numerical analysis techniques in computing signal or noise subspaces. The algorithm is based on the two step procedures, one for transforming input data to frequency domain data and the other for estimating the unknown TOA using the proposed efficient algorithm. The efficiency in number of operations over other algorithms is presented. The performance of the proposed algorithm is investigated by means of computer simulations.. Throughout the analytic and computer simulation results, we show that the proposed algorithm exhibits superior performance in estimating TOA estimation with limited computational cost.

Key Words : TOA, UWB, Ranging, Minimum Norm, Indoor Channel

1. Introduction

For next-generation location-aware wireless networks, location finding techniques are becoming increasingly important[1]. Location finding based on time-of-arrival(TOA) is the most popular method for accurate positioning systems. The basic problem in TOA-based techniques is to accurately estimate the propagation delay of the radio signal arriving from the direct line-of-sight (DLOS) propagation path. However, in indoor and urban areas, due to severe multipath conditions and the complexity of the radio propagation, the DLOS cannot always be accurately detected[2-3]. Increasing time-domain resolution of channel response to resolve the DLOS path improves the performance of location finding systems employing TOA estimation techniques. Super-resolution techniques have been studied in the field of spectral estimation[4]. Recently, a number of researchers have applied super-resolution spectral estimation techniques for time-domain analysis of different applications. These applications include electronic devices parameter measurement[5-6] and multipath radio propagation studies[7-11]. In[7], the super-resolution technique was

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Date of submit : 2007. 3. 16
First assessment : 2007. 3. 21
Completion of assessment : 2007. 4. 9

employed in the frequency domain to estimate multipath time dispersion parameters such as mean excess delay and root-mean-square delay spread.

Here, we address the application of super-resolution techniques to accurate TOA estimation for indoor geolocation. In the literature, the time-delay estimation problem has been studied with a variety of super-resolution techniques, such as minimum-norm[9], root multiple signal classification(MUSIC)[10], and total least square-estimation of signal parameters via rotational invariance techniques(TLS-ESPRIT)[11]. While super-resolution techniques can increase time-domain resolution, they also increase complexity of system implementation.

In this paper, we present a new robust TOA estimation algorithm which estimates first time arrival in Ultra Wideband(UWB) channel. The proposed algorithm efficiently removes the necessity of finding whole eigenvectors in estimating signal or noise subspaces. The algorithm is based on power method[12], and it is proven that computational cost is reduced dramatically. To verify the performance of the algorithm, computer simulations have been done by changing the parameters.

The rest of the paper is organized as follows. In Section II, general frequency domain TOA algorithms are presented. Then, an efficient TOA estimation algorithm is addressed in Section III. Section IV presents computer simulation results of the proposed algorithm. Finally, conclusions are presented in Section V.

2. FREQUENCY DOMAIN TOA ALGORITHMS

The multipath indoor radio propagation channel is normally modeled as a complex lowpass equivalent impulse response given by

$$h(t) = \sum_{k=0}^{L_p-1} \alpha_k \delta(t - \tau_k) \tag{1}$$

where L_p is the number of multipath components, and $\alpha_k = |\alpha_k| e^{j\theta_k}$ and τ_k are the complex attenuation and propagation delay of the kth path, respectively, while the multipath components are indexed so that the propagation delays, τ_k, $0 \le k \le L_p-1$are in ascending order.

As a result, τ_0 in the model denotes the propagation delay of the DLOS path, i.e., the TOA, which needs to be detected for the purpose of indoor geolocation. Taking the Fourier transform of (1), the frequency-domain channel response can be expressed as

$$H(f) = \sum_{k=0}^{L_p-1} \alpha_k e^{-j2\pi f \tau_k} \tag{2}$$

The parameters α_k and τ_k are random time-variant functions because of the motion of people and equipment in and around buildings. However, since the rate of their variations is very slow as compared with the measurement time interval, these parameters can be treated as time-invariant random variables within one snapshot of measurement[13]. The phase of the complex attenuation θ_k is normally assumed random from one snapshot to another with a uniform probability density function U(0, 2π)[14]. On the other hand, these parameters are frequency-dependent since they are related to radio signal characteristics such as transmission and reflection coefficients. However, as shown in [15], for frequency bands used in this report, these parameters can be assumed frequency-independent. In this paper, we consider super-resolution TOA estimation based on frequency-domain indoor channel response. In practice, discrete samples of frequency-domain channel response can be obtained by sweeping the channel at different frequencies[16], by using a multicarrier modulation technique such as orthogonal frequency-division multiplexing(OFDM), or in a direct-sequence spread spectrum(DSSS) system by deconvolving the received signal over the frequency band of high signal-to-noise ratio[7, 9-11].

If we exchange the role of time and frequency variables in (2), we can observe that it becomes a harmonic signal model

$$H(\tau) = \sum_{k=0}^{L_p-1} \alpha_k e^{-j2\pi f_k \tau} \tag{3}$$

which is well known in the spectral estimation field[4]. Consequently, any spectral estimation techniques that are suitable for the harmonic signal model can be applied to the frequency response of a multipath indoor radio channel to perform time-domain analysis. In this report, we use the MUSIC algorithm[17], as an example of super-resolution techniques, in TOA estimation for indoor geolocation applications.

The discrete measurement data are obtained by sampling channel frequency response H(f) at L equally spaced frequencies. Considering additive white noise in the measurement process, the sampled discrete frequency domain channel response is given by

$$x(l) = H(f_l) + w(l) = \sum_{k=0}^{L_p-1} \alpha_k e^{-j2\pi(f_0 + l\Delta f)\tau_k} + w(l) \tag{4}$$

where l =0,1,...,L-1, and, w(l) denotes additive white measurement noise with mean zero and variance σ^2_w. We can then write this signal model in vector form

$$x = H + w = Va + w \tag{5}$$

where

$$X = [x(0)\ x(1)\ \dots\ x(L-1)]^T$$
$$H = [H(f_0)\ H(f_1)\ \dots\ H(f_{L-1})]^T$$
$$W = [w(0)\ w(1)\ \dots\ w(L-1)]^T$$
$$V = [v(\tau_0)\ v(\tau_1)\ \dots\ v(\tau_{L_p-1})]$$
$$v(\tau_k) = [1\ e^{-j2\pi\Delta f \tau_k}\ \dots\ e^{-j2\pi(L-1)\Delta f \tau_k}]^T$$
$$a = [\alpha'_0\ \alpha'_1\ \dots\ \alpha'_{L_p-1}]^T$$
$$\alpha'_k = \alpha_k e^{-j2\pi f_0 \tau_k}$$

and the superscript T denotes the matrix transpose operation.

The MUSIC super-resolution techniques are based on eigen-decomposition of the auto-correlation matrix of the preceding signal model in (5)

$$R_{xx} = E\{xx^H\} = VAV^H + \sigma^2{}_w I \tag{6}$$

where the superscript H denotes conjugate transpose operation, i.e., Hermitian, of a matrix.

Since the propagation delays τ_k in (1) can be theoretically assumed all different, and the matrix V has full column rank, i.e., the column vectors of V are linearly independent. If we assume the magnitude of the parameters α_k is constant and the phase is a uniform random variable in[0, 2π], the L_p x L_p covariance matrix A is nonsingular. Then, from the theory of linear algebra, it follows that assuming L > L_p, the rank of the matrix VAV^H is L_p, or equivalently, the L-L_p smallest eigenvalues of R_{xx} are all equal to σ^2_w. The eigenvectors(EVs) corresponding to L-L_p smallest eigenvalues of R_{xx} are called noise EVs, while the EVs corresponding to L_p largest eigenvalues are called signal EVs. Thus, the L-dimensional subspace that contains the signal vector x can be split into two orthogonal subspaces, known as signal subspace and noise subspace, by the signal EVs and noise EVs, respectively. The projection matrix of the noise subspace is then determined by (7).

$$P_{\omega} = Q_w (Q_w{}^H Q_w)^{-1} Q_w{}^H = Q_w Q_w{}^H \qquad (7)$$

where and Qw=[q_{L_p} q_{L_p+1} $\cdots$ q_{L-1}] are q_k, $L_p \le k \le L-1$ are noise EVs. Since the vector $v(\tau_k)$, $0 \le k \le L_p-1$ must lie in the signal subspace, we have

$$P_w v(\tau_k) = 0 \qquad (8)$$

Thus, the multipath delays τ_k, $0 \le k \le L_p-1$ can be determined by finding the delay values at which the following MUSIC pseudospectrum achieves maximum value :

$$S_{MUSIC}(\tau) = \frac{1}{\| P_w v(\tau) \|^2} = \frac{1}{V^H(\tau) P_w v(\tau)} = \frac{1}{\| Q_w{}^H v(\tau) \|^2} = \frac{1}{\sum_{k=L_p}^{L-1} | q_k{}^H v(\tau) |^2} \qquad (9)$$

One implicit assumption in the MUSIC method is that the noise eigenvalues are all equal, i.e., $\lambda_k = \sigma^2 \omega$ for $L_p \le k \le L-1$, that is, the noise is white. However, as we just discussed, when the correlation matrix is estimated from a limited number of data samples in practice, the noise eigenvalues are not equal. A slight variation on the MUSIC algorithm, known as the EV method, can be used to account for the potentially different noise eigenvalues[4], [132]. The pseudospectrum of the EV algorithm is defined as

$$S_{EV}(\tau) = \frac{1}{\sum_{k=L_p}^{L-1} \frac{1}{\lambda_k} | q_k{}^H v(\tau) |^2} \qquad (10)$$

where λ_k, $L_p \le k \le L-1$, are the noise eigenvalues. In effect, the pseudospectrum of each EV is normalized by its corresponding eigenvalue. If the noise eigenvalues are equal, the EV method and the MUSIC method are identical. The performance of the MUSIC and EV methods were compared in[3], and it was shown that the EV method is less sensitive to inaccurate estimate of the parameter L_p, which is highly desirable in a practical implementation. As presented later in this report, the EV method is shown by computer simulations to have slightly better performance than the MUSIC method. In Section IV, we investigate diversity techniques that can be used to further improve the performance of super-resolution TOA estimation techniques.

A slight variation on the MUSIC algorithm, known as the minimum norm algorithm was also presented in the literature. The pseudo-spectrum of the minimum norm algorithm is defined as

$$S_{EV}(\tau) = \frac{1}{a^H v(\tau)} \qquad a = \lambda P_w u_1 \qquad (11)$$

where u1 = [1 0 0 $\cdots$ 0].

Instead of forming an eigenspectrum that uses all of noise eigenvectors as in the MUSIC and eigenvector algorithms, the minimum norm algorithm uses a single vector a that is constrained to lie in the noise space, and the complex exponential frequencies are estimated from the peaks of the frequency estimation SEV(τ).

3. Efficient High Resolution TOA Algorithm

In this section, we propose a new efficient super-resolution algorithm based on minimum norm algorithm. The overall architecture of the proposed algorithm is shown in Figure 1.

The overall flow of the proposed algorithm proceeds as follows :

1) The received signal is passed band-pass filter to reduce the bandwidth.
2) The signal energy is computed.
3) The energy signal is accumulated for 1 to 4μ

seconds.

4) Then the accumulated energy signal is converted to digital signal with AD converter.
5) Accumulation of a few frames follows, resulting in increase of Signal to Noise Ratio (SNR) of signal.
6) The FFT processing is used to convert multipath time delay to corresponding frequency offset.
7) With FFT output, the proposed algorithm is applied to find dominant frequency offset.
8) Finally, TOA is estimated by converting frequency of maximum peak to time delay.

The core of the proposed algorithm is explained afterward. The detailed algorithm block is shown in Figure 2 summarized as follows :

1) FFT block : With this operation, the background noise is suppressed and the coarse multi-path information is converted to frequency component. In moderate SNR condition, the FFT operation does give enough information for clear TOA, whereas in low SNR the information is not enough to locate TOA.
2) Auto-correlation block : The auto-correlation operation is performed via circular convolution which can be done with low computation cost.
3) Principal eigenvector (p) block : principal eigenvector of auto-correlation matrix is computed via power method[20]. The power method is an iterative operation to find the principal eigenvector.
4) Noise subspace block : The noise subspace of the auto-correlation matrix is computed via matrix subtraction described as follows :

$N = I - p*p'$

where I is identity matrix and p is principal eigen-vector.

5) Spectrum Block: The spectrum of the auto-correlation matrix is obtained and plotted.
6) TOA estimation block: The TOA is estimated with the spectrum information obtained.

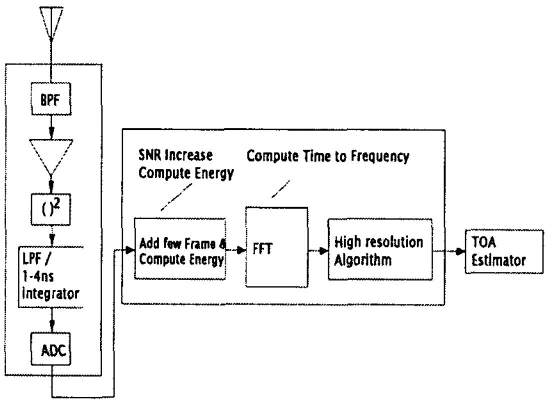

Fig. 1. Overall architecture of the proposed algorithm

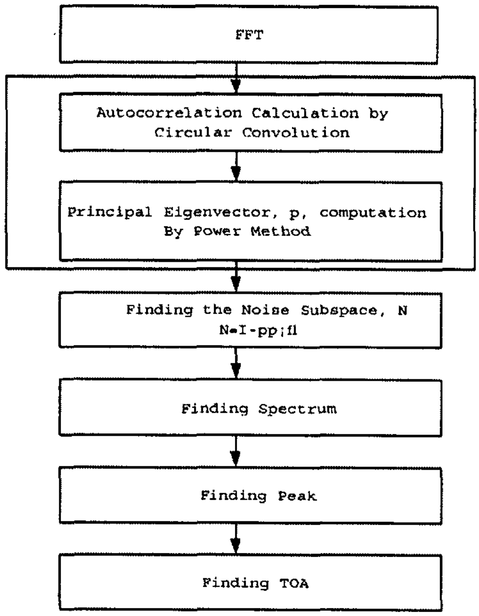

Fig. 2. Overall architecture of the proposed algorithm

Next, we investigate complexity of the proposed algorithm by means of counting the operations needed. The required operations of the algorithm are correlation, FFT and comparison operation. Thus if the number of energy block is N, the total complexity for each operation are as follows :

- Correlation matrix, R : N point Correlation
- FFT : N point FFT
- Noise Subspace Finding : N point scalar and vector multiplication
- Peak Finding operation : N point comparison

With this information, we can summarize the complexity of the proposed algorithm as follows : Table 1.

Table 1. The Complexity Of The Proposed Algorithm

Algorithm	Complexity	N = 32
Accumulation of signal	(Preamble symbols-1) x 31 chip sequence adds.	992 operations. (=32x31,)
N point FFT	2x(N/2)log2N complex multiplications. 2xNlog2N complex additions	960 operations. 640 operations.
Correlation (3times)	3xN*N real multiplication 3xN*(N-1)real addition	3072op.(=3x1024 real mults.) 2976 op.(=3x992 real adds.)
Noise subspace	N complex multiplication	192 op.(=128 real mults. + 64 real add.)
Finding peak	N-1 comparison	31 comparisons
Total operations		8863 op.
Memory size	N	32

If we compare the complexity of the proposed algorithms by Mitsubishi Electric Research Laboratory(MERL) and Institute for Infocomm Research(I^2R)[17], we can obtain the following Tables.

In Table 2, we can obtain the following complexity ratio as:

$$\text{Complexity Ratio} = \text{Propose/MERL} = 8863/9902 = 97.5[\%]$$

If we compare the algorithm with , we obtain the following Table III. With Table III, we can obtain the following complexity ratio as :

$$\text{Complexity Ratio} = \text{Propose}/I^2R = 8863/32209 = 27.4[\%]$$

Table 2. The Complexity Of Merl

Algorithm	Complexity	N=32
NxN image*	(N-2x N-2) x 32 rearrange operations	8100op. (=30x30x32)
2D to 1D conversion	(Preamble symbols-1) x 31chip sequences adds.	992op. (=31x32)
Total operation		9902op.
Memory size	NxN=N2	1024

Table 3. The complexity of I^2R

Algorithm	Complexity	N = 32
Sliding Correlation	N*N real adds.	1024 real adds.
N/2 x N image	sliding orrelation x 31 chip sequences	31744 op. (1024x31)
2D to 1D conversiion	(Preamble sym-1) x 31 chip sequences adds.	465 op. (15 x 31)
Total operation		32209 op. (31744+465)
Memory size	Preamble symbols x 31 chip sequences	496 (16 x 31)

Thus we can conclude that our complexity of algorithm is compatible with MERL and one fourth of I^2R.

4. Simulation results

In this section, we investigate the performance of the super-resolution algorithm by means of computer simulations based on the impulse response of indoor radio propagation channels models[18]. The indoor radio channel is under either LOS or NLOS circumstance. The transmitted signal is generated the IEEE standard as described in[19]. The signal generated by ternary code of length 31 according to nano-second is illustrated in the following Figure 3.

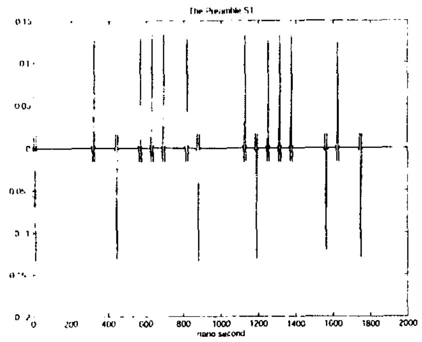

Fig. 3. The transmitted signal

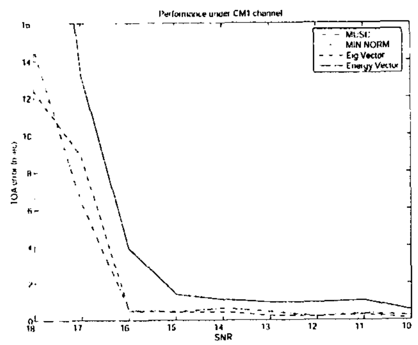

Fig. 4. The Performance under CM1 channel

First, we investigate the performance of the proposed algorithm by using the LOS indoor radio model. The simulation parameters are (1) CM1 Channel (2) Ts = 4ns and (3) Number of framed accumulated is 10.

The performance of the proposed minimum norm based algorithm with MUSIC, EV and energy based algorithm, i.e MERL, is shown in Figure 4. As seen in Figure 4, we can observed that TOA estimation error versus SNR is clearly less than the energy based algorithm. Also, the performance of the proposed algorithm exhibits almost the same results as MUSIC and EV.

Next, we present the results when interference is presented. For simulation, we add one interference of which power is equal to the signal by using another ternary code. The performance of the proposed minimum norm based algorithm with MUSIC, EV and energy based algorithm according to SNR is shown in Figure 5. As seen in Figure 5, we can observe that the proposed algorithm shows better performance than the energy based algorithm, i.e, MERL. Also, the performance of the proposed algorithm is robust to interference which is a major merit of frequency domain algorithms such as MUSIC, Minimum Norm and EV.

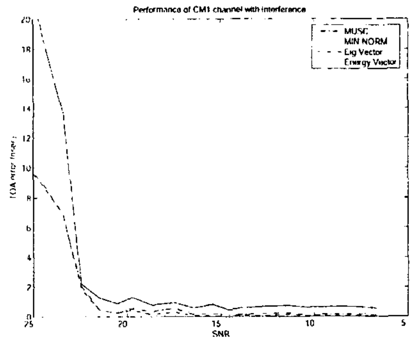

Fig. 5. The Performance under CM1 channel when interference is presented

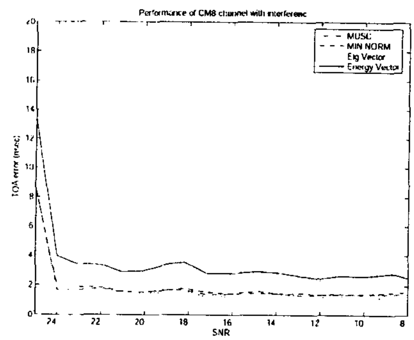

Fig. 6. The Performance under CM8 channel when interference is presented

Second, we investigate the performance of the proposed algorithm by using the NOS indoor radio model. The simulation parameters are

(1) CM8 channel is considered (2) Ts = 4ns (3) Number of framed accumulated equals 20.

The performance of the proposed minimum norm based algorithm with MUSIC, EV and energy based algorithm according to SNR is shown in Figure 6. As seen in Figure 6, the proposed method exhibits robustness to background noise and interference. However, the bias of error is rather than the case of CM1 case, which can be expected.

5. Conclusion

In this paper, we present a novel and numerically efficient algorithm for high resolution TOA estimation which can be used either in coherent or non-coherent receivers.

The proposed TOA estimation algorithm is based on Minimum norm algorithm, and the efficiency of the proposed algorithm relies on computing signal and noise subspaces.

The performance of the proposed algorithm is investigated by means of computer simulations. Throughout the simulations, it is shown that the proposed algorithm can significantly improve the performance of TOA estimation, and it is robust to background noise and NLOS as well as LOS channel condition. Also, we present the computational complexity results by comparing the algorithms in[17]. With the quantitative analysis of the operation, the computational complexity of the algorithm is proven to be compatible to MERL and is one fourth of the I^2R. Thus the proposed algorithm can be an excellent candidate for receivers of ranging estimation capability.

This work was supported by a research grant of Cheju National University in 2006.

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Biography

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