Discrete Multi-Wavelet 변환을 이용한 LMS기반 적응 등화기 설계

최윤석* · 박형근**

Design of LMS based adaptive equalizer using Discrete Multi-Wavelet Transform

Yun-Seok Choi* · Hyung-Kun Park**

요 약

차세대 이동 멀티미디어 통신에서는 전송지연을 줄이고 버스트 시변채널의 시간변화를 제한하기 위해 버스트 전송이 많이 사용된다. 그러나 채널적응을 위한 훈련 심볼은 짧은 길이의 버스트 데이터에 대해 심각한 문제를 야기할 수 있다. 따라서 심볼에 대한 적응 등화기의 설계에 있어서 짧은 길이의 훈련 심볼과 빠른 수렴을 갖는 적응 알고리즘이 필요로 된다. 본 논문에서는 DMWT (discrete multi-wavelet transform)과 LMS(least mean square) adaptation 을 갖는 적응 등화기를 제안한다. 제안된 등화기는 복잡성의 증가를 최소화하면서도 현재의 transform-domain equalizer보다 빠른 수렴을 갖는다.

ABSTRACT

In the next generation mobile multimedia communications, the broad band short-burst transmissions are used to reduce end-to-end transmission delay, and to limit the time variation of wireless channels over a burst. However, training overhead is very significant for such short burst formats. So, the availability of the short training sequence and the fast converging adaptive algorithm is essential in the system adopting the symbol-by-symbol adaptive equalizer. In this paper, we propose an adaptive equalizer using the DWMT (discrete multi-wavelet transform) and LMS (least mean square) adaptation. The proposed equalizer has a faster convergence rate than that of the existing transform-domain equalizers, while the increase of computational complexity is very small.

키워드

wavelet transform, least mean square, adaptive equalizer, DMWT

Ⅰ. Introduction

A key issue toward next generation mobile multimedia communications is to create technologies for broadband signal transmission that can support high quality services. In such a broadband mobile communications system, the transmitted signal will be distorted severely by the time-varying multi-path fading channel [1], [2]. Therefore, a desired system should be designed to reject the severe inter-symbol interference (ISI) caused by multi-path propagation and to be robust to time-varying fading, while providing high spectral efficiency and low power

* 삼성전자 네트워크사업부

** 한국기술교육대학교 정보기술공학부, 교신저자

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consumption.

In order to reduce the distortion due to ISI, the symbol-by-symbol adaptive equalization device can be considered. A good adaptive algorithm should attain the properties of the fast converging performance and the low complexity to achieve high spectral efficiency and the robustness to fast time-varying fading. The recursive least squares (RLS) type algorithms have been used commonly since these algorithms can provide a fast converging property. But, these algorithms require high computational complexity and, as a consequence, the RLS based equalizer consumes a large amount of the computational power at the receiver. By contrast, the LMS algorithm has the low computational complexity. But, when the LMS algorithm is adopted, the convergence performance depends on the eigen value spread of the input vector autocorrelation matrix. For example, the convergence rate is very slow when the channel characteristics result in an autocorrelation matrix whose eigenvalues have a large spread. In order to speed up the convergence rate, the transform domain LMS (TRLMS) algorithms have been proposed. The existing TRLMS algorithms are as follows; the discrete cosine transform LMS (DCT-LMS), the discrete Fourier transform LMS (DFT-LMS), the M-band discrete single-wavelet transform LMS (DWT-LMS), and the combined TRLMS and Gram-Schmidt orthogonalization algorithm [3]-[7]. These TRLMS algorithms improve the convergence rate by reducing the eigenvalue spread of the input autocorrelation function with a small increase in computational load.

Recently, the discrete multi-wavelet transform (DMWT) has been developed as the new chapter of wavelet theory. While single wavelets use translates and dilates of one mother wavelet function, multi-wavelets use translates and dilates of more than one mother wavelet functions. Multi-wavelets are known to have several advantages over single wavelets such as orthogonality, symmetry, short support and a high number of vanishing moments. DMWT based applications have been introduced in several fields such as image processing and signal compression [8]-[11]. So far DMWT based LMS filtering algorithm and its performance have not been presented in the existing papers. In this paper, the DMWT-LMS based adaptive equalization is proposed, and the values of eigen value spreads are estimated and compared for various algorithms. Throughout the computer simulations, we show the converging performance of the proposed DMWT-LMS based equalizer with the different prefilters, and compare the performance of proposed equalizer with that of conventional equalizers. The complexity of DMWT-LMS algorithms the same as that of DWT-LMS algorithm except the additional addition for the preprocessing procedure.

This paper is organized as follows: In Section II , we show the discrete multi-wavelet transformation, and describe the proposed DMWT-LMS based adaptive equalizer in Section III. Section IV shows the complexity of the proposed scheme. In Section V, computer simulations are executed and their results are discussed. Finally, in Section V, concluding remarks are presented.

Ⅱ. Discrete multi-wavelet transform (DMWT)

While single wavelets (or scalar wavelets) need only one scaling function, multi-wavelets (or vector wavelets) need r scaling functions $\Phi(t)=[\phi_1(t),\cdots,\phi_r(t)]$ and r wavelet functions $\Psi(t)=[\psi_1(t),\cdots,\psi_r(t)]$, where r>1. Multi-wavelets satisfy the dilation and wavelet equations as follows:

$$\Phi(t)=2\sum_{k=0}^{K-1}\mathbf{C}(k)\Phi(2t-k) \tag{1}$$

$$\Psi(t)=2\sum_{k=0}^{K-1}\mathbf{D}(k)\Psi(2t-k) \tag{2}$$

where $\{\mathbf{C}(k)\}_{0\le k\le K-1}$ and $\{\mathbf{D}(k)\}_{0\le k\le K-1}$ are $K\times K$ filter matrices and represent the low pass and high pass filter parameters respectively. The scaling functions $\phi_i(t)$ and associated wavelets $\psi_i(t)$ are constructed so that all the integer translations of $\phi_i(t)$ are orthogonal, and the integer translations and dilations of factor 2 of $\psi_i(t)$ form an orthonormal basis for $L^2(R)$.

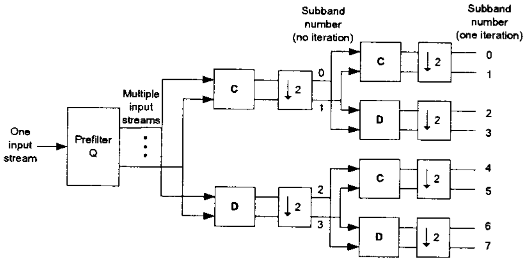

Fig. 1. DMWT using the uniform filterbank structure
그림 1. uniform filterbank구조를 사용한 DMWT

Multi-wavelet transform is also based on the multi-resolution (MRA) analysis as in the single wavelet transform and so can be constructed by iterated filter banks (see Fig. 1). A very important multi-wavelet system is GHM (Geronimo, Hardin, and Massopust) multi-wavelet with $r=2$, which was constructed by Geronimo, Hardin, and Massopust [12]. This system consists of the low pass filter C(k) and the high pass filter D(k)with, respectively, four 2×2 matrices and K=4. The corresponding filter coefficients are given by

$$\mathbf{C}(0)=\begin{bmatrix} 3/10 & 2\sqrt{2}/5 \\ -\sqrt{2}/40 & -3/20 \end{bmatrix} \quad \mathbf{C}(1)=\begin{bmatrix} 3/10 & 0 \\ 9\sqrt{2}/40 & 1/2 \end{bmatrix}$$

$$\mathbf{C}(2)=\begin{bmatrix} 0 & 0 \\ 9\sqrt{2}/40 & -3/20 \end{bmatrix} \quad \mathbf{C}(3)=\begin{bmatrix} 0 & 0 \\ -\sqrt{2}/40 & 0 \end{bmatrix} \qquad (3)$$

and

$$\mathbf{D}(0)=\begin{bmatrix} -\sqrt{2}/40 & -3/20 \\ -1/20 & -3\sqrt{2}/20 \end{bmatrix} \quad \mathbf{D}(1)=\begin{bmatrix} 9\sqrt{2}/40 & -1/2 \\ 9/20 & 0 \end{bmatrix}$$

$$\mathbf{D}(2)=\begin{bmatrix} 9\sqrt{2}/40 & -3/20 \\ -9/20 & 3\sqrt{2}/20 \end{bmatrix} \quad \mathbf{D}(3)=\begin{bmatrix} -\sqrt{2}/40 & 0 \\ 1/20 & 0 \end{bmatrix} \qquad (4)$$

Due to the matrix property of multi-wavelet filter coefficients, the multi-wavelet filter banks need r input streams. Therefore, a method of mapping the one stream input data to the multiple streams has to be developed. This mapping process is called preprocessing and is done by a prefilter Q. Fig. 1 depicts the DMWT using the uniform filter bank followed a prefilter Qand one iteration. The existing prefilters are shown in [10]-[11]:

Xia nonorthogonal prefilter (called 'Xia prefilter') [10]

$$Q=\begin{bmatrix} -0.0917517 & 0.9082483 \\ 0.28867513 & 0.28867513 \end{bmatrix} \qquad (5)$$

Orthogonal prefilter satisfying S-F condition (called 'SF prefilter') [11]

$$Q=\begin{bmatrix} \sqrt{6}/9 & 2\sqrt{6}/9 \\ -\sqrt{3}/9 & 4\sqrt{3}/9 \end{bmatrix} \qquad (6)$$

Ⅲ. DMWT-LMS based adaptive equalization

First, consider a continuous time signal observed at the output of a noisy communication channel

$$x(t)=\sum_{k=-\infty}^{\infty} s_k h(t-kT_s)+w(t) \qquad (7)$$

where $\{s_k\}$ denote the transmitted symbols sequence with the rate 1/Ts and Ts is the symbol duration. h(t) denotes the continuous time channel having the finite support $t\in[0,L_h T)$ and includes the Tx/Rx filter and multi-path propagation. w(t) is additive noise that is assumed to be stationary and uncorrelated with s_k.

The corresponding fractionally spaced discrete time model can be obtained either by sampling the signal received on several sensors at the emission duration, by over-sampling the signal received on a single receiver, or by combining both techniques. Especially, in the application of communications system, the fractionally spaced model can mitigate the effect of the timing error. However, the perfect timing recovery is assumed and so, for convenience, the symbol-spaced discrete time model is considered here. x(t) is sampled at t=nT and then the received data of the length N can be represented in a matrix-vector form as

$$\mathbf{x}(n) = \mathbf{H}\mathbf{s}(n) + \mathbf{w}(n) \quad (8)$$

where x(n) and w(n) are N×1 vectors, H is the $N(N+L_h)$ block Toeplitz Sylvester matrix and s(n) is $(N+L_h)\times 1$ vector, and

$$\mathbf{x}(n) = [x_n(0), x_n(1), \cdots, x_n(N-1)]^T \quad (9)$$

$$\mathbf{s}(n) = [s_n, s_{n-1}, \cdots, s_{n-N-L_h-1}]^T \quad (10)$$

$$\mathbf{w}(n) = [w(n), w(n-1), \cdots, w(n-N+1)]^T \quad (11)$$

$$\mathbf{H} = \begin{bmatrix} h(0) & h(1) & \cdots & h(L_h) & 0 & \cdots & \cdots & 0 \\ 0 & h(0) & h(1) & \cdots & h(L_h) & 0 & \cdots & 0 \\ \vdots & & & \ddots & & \ddots & & \vdots \\ 0 & \cdots & \cdots & 0 & h(0) & h(1) & \cdots & h(L_h) \end{bmatrix} \quad (12)$$

The following throughout is assumed:

- input sequence $\{s_k\}$ is zero mean, and $E[s_k s_l^*] = \delta(k-l)$ where $\delta(t)$ is the discrete-time impulse response.
- noise v(t) is stationary with zero mean, white with variance σ_v^2, and uncorrelated with the input sequence $\{s_k\}$.

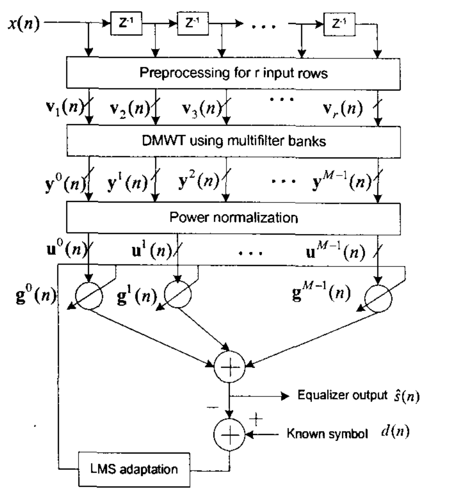

Fig. 2. Block diagram of the DMWT-LMS based adaptive equalizer
그림 2. DMWT-LMS기반의 적응등화기의 블록도

A block diagram of a DMWT-LMS based adaptive equalizer is depicted in Fig. 2 and the procedures are classified into preprocessing for input rows, DMWT using multi-filter banks, power normalization, and LMS adaptation. The followings describe the procedure of DMWT-LMS based adaptive equalizer in Fig. 2.

Preprocessing of input signal:

Let $x_n(i) = x(n-i)$. The received signal vector **x**(*n*) of length N is preprocessed using prefilter Q to get rows vector **v**(*n*) where $\mathbf{x}(n)=[x_n(0), x_n(1), ..., x_n(N\text{-}1)]^T$, $\mathbf{v}(n)=[\mathbf{v}_n(0)^T, ..., \mathbf{v}_n(p\text{-}1)^T]^T$ and $\mathbf{v}_n(l)=[\mathrm{v}_{1,n}(l),.., \mathrm{v}_{r,n}(l)]^T$ for $l=0,...,p\text{-}1$ and $p=N/R$. Note that $r=2$ for GHM multi-wavelet. Note that the length N of the input signal vector **x**(*n*) should be greater than r×K. For example, because r=2 and K=4 for GHM multi-wavelet, N is greater than 8.

Multi-wavelet transform using multi-filter bank:

The transformed vector $y(n)$ is given by multiplying the orthogonal multi-wavelet transform matrix $\mathbf{T}_N$ to input rows vector **v**(*n*), i.e. $\mathbf{x}(n)=\mathbf{T}_N\mathbf{v}(n)$ where, for M-band MRA, $y(n)=[y^0(n),..., y^{M-1}(n)]^T$ and $y^j(n)=[y^j{}_0(n),..., y^j{}_{R-1}(n)]$ where the index j is the scale (the subband number, j=0, ..., M-1, and R is the length of j-th subband output vector $y^j(n)$. The transform matrix $\mathbf{T}_N$can be constructed by double shifting N×N matrix as in DWT. For example, if the GHM multi-wavelet and the input signal of length 8 are considered, then the transform matrix $\mathbf{T}_N$ for a 2 band multi-filter bank is given by

$$\mathbf{T}_N = \begin{bmatrix} \mathbf{C}(0) & \mathbf{C}(1) & \mathbf{C}(2) & \mathbf{C}(3) \\ \mathbf{C}(2) & \mathbf{C}(3) & \mathbf{C}(0) & \mathbf{C}(1) \\ \mathbf{D}(0) & \mathbf{D}(1) & \mathbf{D}(2) & \mathbf{D}(3) \\ \mathbf{D}(2) & \mathbf{D}(3) & \mathbf{D}(0) & \mathbf{D}(1) \end{bmatrix} \quad (13)$$

Note that **C**(*n*) and **D**(*n*) are 2×2 matrices and so the resulting matrix $\mathbf{T}_N$ is fourth times shifting 8×8 matrix.

Power normalization:

The *i*-th element $u_i^j(n)$ of the power-normalized output $\mathbf{u}^j(n)$ in j-th subband at n-th iteration can be represented by

$$u_i^j(n) = \frac{y_i^j(n)}{\sqrt{\varepsilon + P_i^j(n)}} \quad i = 0,\cdots,R-1,\ j = 0,\cdots,M-1 \tag{14}$$

where $p_i^j(n)$ is the instantaneous power estimate of $v_i^j(n)$ and ε is a small constant that eliminate overflow when the values of $p_i^j(n)$ are very small. For computing the values of $p_i^j(n)$, the exponential weighted method was used as follows:

$$P_i^j(n) = \beta P_i^j(n) + (1-\beta)\,|\,y_i^j(n)\,|^2 \tag{15}$$

where β is the forgetting factor between 0 and 1.

LMS adaptation:

The update equation of equalizer tap coefficient $g_i^j(n)$ is given by

$$g_i^j(n+1) = g_i^j(n) + \mu u_i^j(n) e^*(n) \tag{16}$$

where $\mu$is the step size, and e(n)is the error signal computed by

$$e(n) = d(n) - \hat{s}(n) = d(n) - \sum_j \sum_i g_i^j(n) u_i^j(n) \tag{17}$$

where d(n)is the known symbol and $\hat{s}_n$ is the equalizer output.

Ⅳ. Complexity considerations

The increase in computational complexity of the TRLMS algorithms mainly comes from the transform processing as compared with the normalized LMS (NLMS) algorithm. The DFT has a $O(n\log_2 N)$ computational complexity and the DWT has a $O(mN)$ computational complexity [3], where O(·) is used in describing the computational complexity of algorithm, and m is the length of wavelet filter coefficients. The complexity of DWT can be reduced from $O(mN)$ to $O(mM)$ by using the redundancy-removal (RR) technique [5]. Note that when $N >> m > M$, the RR method practically the same computational complexity as the TDLMS algorithm. Like a DWT, the DMWT has a $O(\tilde{m}M)$ computational complexity with an additional addition for the preprocessing procedure where $\tilde{m}$ is the average length of filter coefficients. So, the computational increase of DMWT-LMS based equalizer is still very small compared with DWT-LMS based equalizer.

Ⅴ. Simulation and Results

A. Simulation Model

Two ISI channels, given in [1], are considered: one is the minimum phase channel with the z-transform $H_1(z) = 0.84 + 0.53z^{-1}$ and the other is the non-minimum phase channel with the z-transform $H_1(z) = 0.407 + 0.815z^{-1} + 0.407z^{-2}$. Total channel impulse response includes the channel impulse response h(t) and non-ideal pulse shaping filter using the square root raised cosine filter with roll-off factor of 0.3 and support $[-3T_s, 2T_s)$ where T_s is symbol duration. Note that the linear FIR equalizer was implemented for $h_1(t)$ and the decision feedback equalizer (DFE) was implemented for $h_2(t)$. The reason is that the linear FIR equalizer cannot cancel severe ISI channel $h_2(t)$ under the desired level [1]. The DFE consists of two filters, a feedforward filter (FFF) and a feedback filter (FBF). The input to the FFF is the received signal, while the input to the FBF isthe sequence of decisions on previously detected symbols. Functionally, the FBF is used to remove that part of the ISI from the present estimate caused by previously detected symbols. In this way, ISI is eliminated without enhancement of noise [1],[2]. For DWT-LMS based equalization, the

Daubechies wavelet of length 4 (D4) was used and the uniform filter bank structure with 4-band decomposition was constructed. For DMWT-LMS based equalization, the GHM multi-wavelet was used and the uniform multi-filter bank without iteration was constructed. In addition, the Xia and the SF prefilters were constructed.The length of input signal is 8. A QPSK signal was used and the SNR was 25dB. The length of FFF is 8 and the length of FBF (only used to a DFE) is 3. For a fair comparison, the normalized LMS (NLMS) algorithm was also tested.

B. Simulation Results

In this section, the performance of the DMWT-LMS based adaptive DFE with the different prefilters is compared with the existing TDLMS and TRLMS based DFEs via computer simulations.

The convergence behavior of the TRLMS based equalizer based on approximating the autocorrelation matrix of the transformed data as a diagonal matrixhas been analyzed. However, it is noted that the residual correlation varies depending on the characteristics of the input data and on the transform used. The values of eigenvalue spreads are estimated and compared for various algorithms in Table 1 and Fig.3~4. As shownin Fig 3 and 4, the TRLMS algorithms can reduce the eigenvalue spreads, which depends on the transform used. It is shown that the DMWT-LMS based equalizer with the orthogonal SF prefilter can achieve the smallest eigenvalues for both channels.

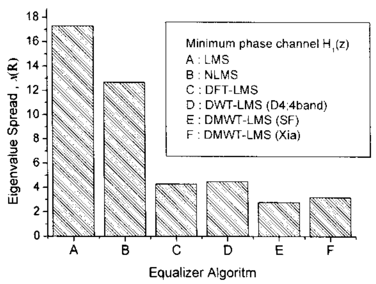

Fig. 3 Eigen value spread for various algorithms under the minimum phase channel $H_1(z)$
그림 3. $H_1(z)$ 채널에서 알고리즘에 따른 Eigen value spread

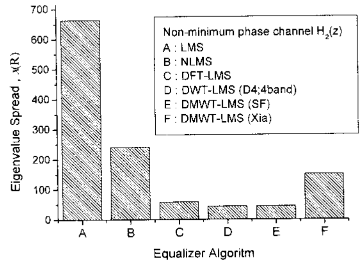

Fig.4 Eigen value spread for various algorithms under the non-minimum phase channel $H_2(z)$
그림 4. $H_2(z)$ 채널에서 알고리즘에 따른 Eigen value spread

Table 1 The comparisons of the values of eigen value spreads for various algorithms
표 1. 서로다른 알고리즘에 대한 eigen value의 비교

$\chi(\mathbf{R})$	LMS	NLMS	DFT-LMS	DWT-LMS (D4; 4band)	DMWT-LMS	
					SF	Xia
$H_1(z)$	17.3	12.7	4.3	4.5	2.8	3.2
$H_2(z)$	662.9	240.1	58.1	43.4	44.1	150.4

Figs. 5 and 6 represent the comparisonsof convergence rate for all algorithms in $h_1(t)$ and $h_2(t)$, respectively. The curves are obtained by taking an ensemble average of 100 statistically independent experiments. In Fig. 5,it is shown that the DMWT-LMS based equalizer with the Xia and SF prefilters yields the better performance than that of the conventional equalizers in convergence rate. In Fig. 6, it is shown that the DMWT-LMS based equalizer with the SF prefilter yields the best performance in convergence rate.

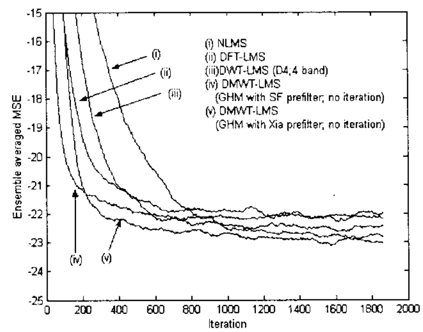

Fig. 5 Convergence comparisons of various adaptive algorithms at minimum phase channel $h_1(t)$
그림 5. $h_1(t)$ 채널에서 알고리즘에 따른 수렴성능비교

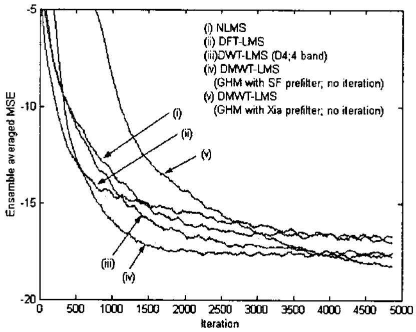

Fig. 6 Convergence comparisons of various adaptive algorithms at non-minimum phase channel $h_2(t)$
그림 6. $h_2(t)$ 채널에서 알고리즘에 따른 수렴성능비교

Ⅵ. Conclusion

In this chapter, a DMWT-LMS based equalizeris proposed to achieve the faster convergence speed. In the proposed equalizer, the choice of the prefilter affects the converging performance. Simulation results demonstrate that the proposed equalizer with the SF prefilter has the better converging performance than that of the conventional equalizers for both minimum and non-minimum phase channels. The computational complexity of the DWT-LMS based equalizer has a very small increase compared with that of the conventional NLMSbased equalizer. In addition, the redundancy removalmethod can further reduce the complexity of DWT-LMS algorithm from $O(mN)$ to $O(mM)$. The DMWT-LMS basedequalizer needs only the additional computation of preprocessing procedure compared with DWT-LMS, e.g. the N additions for the Xia prefilter. Therefore the computational complexity of the new still has a very small increase.

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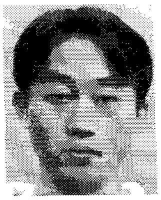

최 윤 석(Yun Seok Choi)

1997년 2월 고려대학교 전자 공학과 졸업
1999년 8월 고려대학교 전자 공학과 석사
2004년 2월 : 고려대학교 전자공학과 박사
2004년 3월 ~현재 : 삼성전자 정보통신총괄 네트워크사업부 책임연구원
※관심분야 : 디지털 통신 시스템, 이동무선통신

박 형 근(Hyung-Kun Park)

1995년 2월고려대학교 전자공학과 (공학사)
1997년 2월고려대학교 전자공학과 (공학석사)
2000년 8월고려대학교 전자공학과 (공학박사)
2000년 9월~2001년 8월: University of Colorado at Colorado Springs, Postdoc.
2001년 9월~2004년 2월: 현대시스콤, 선임연구원
2004년 3월~현재 : 한국기술교육대학교 정보기술공학부 조교수
※관심분야 : 4세대 이동통신, OFDM, 무선자원관리