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충격성 잡음하에서 오차 분포에 기반한 알고리듬의 성능향상

Performance Enhancement of Algorithms based on Error Distributions under Impulsive Noise

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요 약

오차 신호에 대해 가우시안 커널이 가지는 과도신호 차단효과를 기반으로 설계된 오차분포와 델타함수 사이의 유클리드 거리(ED)가 충격성 잡음하에서 효과적인 성능준거로 사용되어왔다. ED의 최소화 과정에서 필요한 기울기는 두 가지 성분, 즉, 오차 쌍의 커널 함수에 대한 성분A_k와 오차 샘플 자체의 커널함수에 대한 성분 B_k를 가진다. 이 논문에서는 성분 A_k가 오차 샘플들을 서로 결집시키는 역할과 관련되어 있으며, 성분 B_k는 오차샘플들의 결집위치가 영(0)이 되는 문제와 관련되어 있다고 분석되었다. 이 분석에 기반하여, 이 논문에서는 오차 샘플간 간격을 좁히는 역할을 강화하고자 A_k를 커널 통과된 오차쌍의 전력으로 정규화하고, 오차 샘플들을 0점에 당기는 역할을 강화하고자 B_k를 커널 통과된 오차샘플 자체의 전력으로 정규화하는 방안을 제안하였다. 충격성 잡음과 다중경로 페이딩 채널 환경하에서 시뮬레이션을 시행하여, 정상상태의 MSE 가지는 흔들림 정도와 최소 MSE 값을 비교 분석하였다. 그 결과, 제안된 방식이 가지는 효용성과 두 성분의 역할이 분석과 일치함이 규명되었다

주제어: 성분, 오차 분포, 델타함수, 유클리드 거리, 충격성 잡음.

ABSTRACT

Euclidean distance (ED) between error distribution and Dirac delta function has been used as an efficient performance criterion in impulsive noise environmentsdue to the outlier-cutting effect of Gaussian kernel for error signal. The gradient of ED for its minimization has two components; A_k for kernel function of error pairs and the other B_k for kernel function of errors. In this paper, it is analyzed that the first component is to govern gathering close together error samples, and the other one B_k is to conduct error-sample concentration on zero. Based upon this analysis, it is proposed to normalize A_k and B_k with power of inputs which are modified by kernelled error pairs or errors for the purpose of reinforcing their roles of narrowing error-gap and drawing error samples to zero. Through comparison of fluctuation of steady state MSE and value of minimum MSE in the results of simulation of multipath equalization under impulsive noise, their roles and efficiency of the proposed normalization method are verified.

☞ Keyword: Components, Error distribution, Delta function, Euclidean distance, Impulsive noise.

1. INTRODUCTION

Weight adjusting algorithms in the adaptive signal processing area are derived through minimizing or maximizing a chosen performance criterion [1]. One of well-known performance criteria, the MSE (mean squared error) measures the average of the squares of the error signal which is the difference between the reference signal and the system output. The averaging process ofsquared error samples can mitigate the effects of the Gaussian noise. In impulsive noise environments, however, the averaging effect is defeated since a single large, impulse noise sample can dominate these sums.

Unlike the MSE-based learning methods, the information-theoretic learning (ITL) is based on the information potential concept that data samples can be treated as physical particles in a potential field so that they interact with each other by information forces [2]. The ITL method is expressed usually as probability distribution functions constructed by the kernel density estimation method with the Gaussian kernel [3].

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As one of ITL criteria, Euclidian distance (ED) between two distributions obtained from biomedical data sets has been successfully applied for supervised training of adaptive systems for medical diagnosis [4]. For FIR (finite impulse response) adaptive filter structures in impulsive noise environments,ED between error distribution and Dirac delta function has been used an efficient performance criterion taking advantage of the outlier-cutting effect of Gaussian kernel for error signal [5]. In this approach with error distribution and delta function, minimization of the ED (MED) has led to adaptive algorithms that adjust weights so as for the error distribution to match a delta function, that is, error samples concentrate on zero [6].

This MED algorithm has a drawback of heavy computational burden due to the double summation operations at each iteration time for the estimation of its gradient. But this burden has been significantly reduced by employing a recursive gradient estimation method [7].

The gradient in ED minimization process of the MED algorithm has two components; one for kernel function of error pairs and the other for kernel function of error themselves. The roles of these two components have not been analyzed or experimented in scientific literatures.

In this paper, we analyze the roles of the two components and based on the analysis, we propose a method of normalizing those components with power of modified inputs. Through simulation in multipath channel equalization under impulsive noise, their roles of managing error samples are verified and it is shown that the proposed method of normalization significantly reduces misadjustment and lowers steady state MSE in impulsive noise environment.

2. MSE AND EUCLIDEAN DISTANCE OF ERROR DISTRIBUTIONS

For the structure of tapped delay line (TDL) with the input vector $\mathbf{X}_k = [x_k, x_{k-1}, ..., x_{k-L+1}]^T$ and weight $\mathbf{W}_k$ $= [w_{0,k}, w_{1,k}, ..., w_{L-1,k}]^T$ at time k, the output y_k becomes $y_k = \mathbf{W}_k^T \mathbf{X}_k$. Letting d_k be the desired signal, the error signal is $e_k = d_k - y_k$ and commonly used in performance criteria or cost functions. The mean squared error (MSE) criterion as one of the most widely used criteria is statistical average $E[\cdot]$ of error power e_k^2, that is, $MSE = E[e_k^2]$. For practical implementation we can use the instant squared error (ISE) e_k^2 as a cost function. Minimization of this ISE, adopting the gradient $\frac{\partial e_k^2}{\partial \mathbf{W}} = -2e_k \mathbf{X}_k$ and a step size μ_{LMS} leads to the least mean square (LMS) algorithm [1].

$$\mathbf{W}_{k+1} = \mathbf{W}_k - \mu_{LMS} \frac{\partial e_k^2}{\partial \mathbf{W}} = \mathbf{W}_k + \mu_{LMS} 2e_k \mathbf{X}_k \tag{1}$$

We can observe in (1) that a single large error sample induced from impulsive noise can generate a big weight perturbation $\mathbf{W}_{k+1} - \mathbf{W}_k$. The perturbation becomes zero only when the error e_k is zero. So we can predict that the weight update process (1) can be unstable in impulsive noise environment.

Unlike the MSE based on the second order information of error power, the error distribution function can be used in constructing performance criterion. The error distribution function $f_E(e)$ can be derived non-parametrically by using the kernel density estimation method with Gaussian kernel $G_\sigma(e) = \frac{1}{\sigma\sqrt{2\pi}} \exp[\frac{-e^2}{2\sigma^2}]$ and error samples $\{e_k, e_{k-1}, \cdots, e_{k-N+1}\}$ where N is the sample size and σ is the kernel size [3].

$$f_E(e) = \frac{1}{N} \sum_{i=k-N+}^{k} G_\sigma(e - e_i) \quad . \tag{2}$$

As a performance criterion, the Euclidean distance $ED[f_E(e), \delta(e)]$ of error distributions for FIR filtering has been introduced in [5], where the distance $ED[f_E(e), \delta(e)]$ is defined as the distance between the distribution of error signal $f_E(e)$ and a Dirac-delta function $\delta(e)$.

$$ED[f_E(e), \delta(e)] = \int [f_E(e) de - \int \delta(e)]^2 de$$
$$= \int f_E^2(e) de + \int \delta^2(e) de - 2 f_E(0) . \tag{3}$$

Minimization of $ED[f_E(e),\delta(e)]$ (MED) forces the distribution of system error $f_E(e)$ to become a shape of impulse function $\delta(e)$ located at zero. This implies that system error samples are forced to become zero.

The fact that the term $\int\delta^2(e)de$ in (3) which is not adjustable can be treated as a constant c leads ED to

$$ED[f_E(e),\delta(e)] = \int f_E^2(e)de + c - 2f_E(0). \tag{4}$$

For minimization of $ED[f_E(e),\delta(e)]$ with respect to $\mathbf{W}$, we have

$$\left.\frac{\partial ED[f_E(e),\delta(e)]}{\partial \mathbf{W}}\right|_k = A_k - B_k, \tag{5}$$

where

$$A_k = \left.\frac{\partial \int f_E^2(e)de}{\partial \mathbf{W}}\right|_k$$
$$= \frac{1}{2\sigma^2 N^2}\sum_{i=k-N+1}^{k}\sum_{j=k-N+1}^{k}(e_j - e_i)$$
$$\cdot G_{\sigma\sqrt{2}}(e_j - e_i)\cdot(\mathbf{X}_j - \mathbf{X}_i)\ , \tag{6}$$

$$B_k = 2\left.\frac{\partial f_E(0)}{\partial \mathbf{W}}\right|_k = \frac{2}{\sigma^2 N}\sum_{i=k-N+1}^{k} e_i \cdot G_\sigma(e_i)\cdot \mathbf{X}_i\,. \tag{7}$$

Then the resulting algorithm with the step size μ_{MED} becomes

$$\mathbf{W}_{k+1} = \mathbf{W}_k - \left.\frac{\partial ED[f_E(e),\delta(e)]}{\partial \mathbf{W}}\right|_k$$
$$= \mathbf{W}_k - \mu_{MED}A_k + \mu_{MED}B_k\,. \tag{8}$$

For the convenience's sake, this algorithm will be referred to in this paper as MED algorithm.

3. GRADIENT ANALYSIS AND INPUT CONTROL BY KERNELLED ERROR

With The term $(e_j - e_i)$ in A_k of (6) means the distance between the two error samples, that is, how far the two errors are located from each other. The error pair $(e_j - e_i)$ may be considered to have some information as to the extent of spread of error samples. Based on the fact that entropy is defined as a measure of how evenly energy is spread or how far apart the positions of components of a system are, this information of error-sample gap $(e_j - e_i)$ can be considered as being related with error entropy. Through the minimization of $ED[f_E(e),\delta(e)]$, that is, the minimization of $\int f_E^2(e)de$, the error gap $e_{j,i} = e_j - e_i$ in A_k becomes zero so that the error samples are forced to come close to each other. This indicates that A_k contributes to narrowing the gap between error samples, though it is uncertain where the error samples are heading.

Since the B_k in (5) plays in reverse direction of A_k as in the minimization of $-2f_E(0)$ of $ED[f_E(e),\delta(e)]$, that is, in the maximization of $2f_E(0)$, the error sample e_i in (7) is forced to be concentrated on zero. Now it becomes certain where the error samples are heading due to B_k.

In short, A_k is involved in minimization of spreading of error samples and B_k takes part in maximization of error-sample concentration on zero. From this point of view, we may regard that B_k plays a role of lowering minimum MSE and A_k is related with lowering misadjustment or fluctuation of minimum MSE.

Similar to the above analysis of error gap, the term $(\mathbf{X}_j - \mathbf{X}_i)$ in A_k means a distance between the two input vector $\mathbf{X}_i$ and $\mathbf{X}_j$ in the input vector space. Letting $\mathbf{X}_{j,i}$ be the input pair $(\mathbf{X}_j - \mathbf{X}_i)$, the term $\mathbf{X}_{j,i}$ may be considered to have some information about the extent of spread of input vectors. That can have us refer to $\mathbf{X}_{j,i}$ as input gap that may also be related with input entropy. Then, A_k can be rewritten as

$$A_k = \frac{1}{2\sigma^2 N^2}\sum_{i=k-N+1}^{k}\sum_{j=k-N+1}^{k} e_{j,i}$$
$$\cdot G_{\sigma\sqrt{2}}(e_{j,i})\cdot \mathbf{X}_{j,i}\,. \tag{9}$$

We observe that the gradient A_k in (5) and (6) is very similar to $\frac{\partial e_k^2}{\partial \mathbf{W}} = -2e_k\mathbf{X}_k$ in (1) in the aspect of error and input terms. It can be noticed that A_k comprises summations of error-gap values and input-gap vectors while the LMS has just an error and an input vector. This observation gives us an insight that e_k of MSE criterion can be corresponding to error gap $e_{j,k}$, and $\mathbf{X}_k$ of MSE criterion can be to $G_{\sigma\sqrt{2}}(e_{j,k})\mathbf{X}_{j,k}$ as a modified input-gap vector. This modified input $G_{\sigma\sqrt{2}}(e_{j,k})\mathbf{X}_{j,k}$ in A_k is actually magnitude controlled by kernelled error-gap, so that it will be referred to in this paper as an input controlled by kernelled error-gap (ICKEG).

$$\mathbf{X}_{j,k}^{ICKEG} = G_{\sigma\sqrt{2}}(e_{j,k})\mathbf{X}_{j,k}. \tag{10}$$

In an element expression,

$$x_{j,k}^{ICKEE} = G_{\sigma\sqrt{2}}(e_{j,k})x_{j,k} = G_{\sigma\sqrt{2}}(e_{j,k})(x_j - x_k) \tag{11}$$

Then, A_k becomes

$$A_k = \frac{1}{2\sigma^2 N^2}\sum_{i=k-N+1}^{k}\sum_{j=k-N+1}^{k} e_{j,i}\mathbf{X}_{i,j}^{ICKEG}. \tag{12}$$

On the other hand, the term $G_\sigma(e_k)\ \mathbf{X}_k$ in (7) can be viewed as a modified input which is controlled by kernelled error. Similar to (10), this modified input in B_k will be referred to as ICKE (input controlled by kernelled error).

$$\mathbf{X}_k^{ICKE} = G_\sigma(e_k)\ \mathbf{X}_k. \tag{13}$$

Then, B_k becomes

$$B_k = 2\left.\frac{\partial f_E(0)}{\partial \mathbf{W}}\right|_k = \frac{2}{\sigma^2 N}\sum_{i=k-N+1}^{k} e_i \cdot G_\sigma(e_i)\cdot \mathbf{X}_i$$
$$= \frac{2}{\sigma^2 N}\sum_{i=k-N+1}^{k} e_i \cdot \mathbf{X}_i^{ICKE}. \tag{14}$$

We can observe that the weight perturbation $\mathbf{W}_{k+1} - \mathbf{W}_k = -\mu_{MED}A_k + \mu_{MED}B_k$ in (8) contains $G_{\sigma\sqrt{2}}(e_{j,k})$ and $G_\sigma(e_k)$ in ICKEG of A_k and ICKE of B_k, respectively. This implies that large error-gap values or large error samples induced from impulsive noise can be transformed to significantly mitigated values through the Gaussian kernel. Therefore the perturbation becomes small even when the error-gap values or error samples are very large as well as small. So we can anticipate that the MED algorithm (8) has very low weight perturbation in impulsive noise environment.

4. POWER ESTIMATION OF MODIFIED INPUT FOR NORMALIZATION

For the purpose of minimizing weight perturbation $\|\mathbf{W}_{k+1} - \mathbf{W}_k\|^2$ of the LMS algorithm in (1), the NLMS (normalized LMS) algorithm has been introduced where the step size is normalized by the averaged power of the current input samples $\|\mathbf{X}_k\|^2 = \mathbf{X}_k^T\mathbf{X}_k = \sum_{m=0}^{L-1} x_{k-m}^2$ [1].

Applying this approach to MED we propose in this section to normalize the step size μ_{MED} in some ways. Since we can see that B_k is related with minimum MSE and A_k is associated with fluctuation of minimum MSE, the step size μ_{MED} is no longer necessary to be used commonly in A_k and B_k. This view leads us to have

$$\mathbf{W}_{k+1} = \mathbf{W}_k - \mu_{MED,A}A_k - \mu_{MED,B}B_k, \tag{15}$$

and propose to normalize each step size separately. That is, $\mu_{MED,A}$ is to normalized by the average power $P_A(k)$ from $\mathbf{X}_{j,k}^{ICKEG} = \left[x_{j,k\ N+1}^{ICKEG}, x_{j,k\ N+2}^{ICKEG}, \ldots, x_{j,k}^{ICKEG}\right]^T$ and $\mu_{MED,B}$ is by $P_B(k)$ from $\mathbf{X}_k^{ICKE} = \left[x_{k\ N+1}^{ICKE}, x_{k\ N+2}^{ICKE}, \ldots, x_k^{ICKE}\right]^T$ as

$$\mu_{MED,A} = \frac{\mu_{MED}}{P_A(k)} = \frac{\mu_{MED}}{\frac{1}{N}\sum_{i=k-N+1}^{k}\sum_{j=k-N+1}^{k}\left|x_{i,j}^{ICKEG}\right|^2}, \tag{16}$$

$$\mu_{MED,B} = \frac{\mu_{MED}}{P_B(k)} = \frac{\mu_{MED}}{\frac{1}{N}\sum_{i=k-N+1}^{k}\left|x_i^{ICKE}\right|^2}. \quad (17)$$

Since the average operation $\frac{1}{N}\sum_{i=k-N+1}^{k}$ maynot be effective in defeating the impulsive noise contained in input, the denominators of (16) and(17) can frequently become too small or too big under impulsive noise. This problem may cause the system to be sensitive to impulsive noise. Also the double summation of the denominators places a heavier computational burden on the algorithm. To avoid these problems, tracking the average power $P_A(k)$ and $P_B(k)$ recursively can be employed as

$$P_A(k) = \beta P_A(k-1) + (1-\beta)\sum_{j=k-N+1}^{k}\left|x_{i,j}^{ICKEG}\right|^2 , \quad (18)$$

$$P_B(k) = \beta P_B(k-1) + (1-\beta)\left|x_k^{ICKE}\right|^2 . \quad (19)$$

The recursive estimation of average power in (18) and (19) can be expressed as a z-transformed system $R(z)$ with input $\sum_{j=k-N+1}^{k}\left|x_{i,j}^{ICKEG}\right|^2$ and output power $P_A(k)$. The system $R(z)$ is applied commonly to input $\left|x_k^{ICKE}\right|^2$ and output power $P_B(k)$.

$$R(z) = A(z) = (1-\beta)\frac{z}{z-\beta} \quad (20)$$

The system $R(z)$ is a single-pole low-pass filter with its time constant controlled by the parameter β $(0<\beta<1)$.

The proposed algorithm with the step sizes normalized separately can be summarized as follows;

$$\mathbf{W}_{k+1} = \mathbf{W}_k - \frac{\mu_{MED}}{P_A(k)}A_k + \frac{\mu_{MED}}{P_B(k)}B_k , \quad (21)$$

where $P_A(k)$ and $P_B(k)$ are estimated by (18) and (19), respectively.

5. DISCUSSION AND RESULTS

It has in section 3 been analyzed that A_k is associated with the role of getting error samples close to each other, that is, reducing fluctuation of minimum MSE and B_k is related with error-sample concentration on zero, that is, lowing the minimum MSE. To verify this analysis under the assumption that steady state MSE is close to minimum MSE, we experiment the proposed algorithm with respect to steady state MSE in the following 3 cases.

Case 1)

$$\mathbf{W}_{k+1} = \mathbf{W}_k - \frac{\mu_{MED}}{P_A(k)}A_k + \mu_{MED}B_k , \quad (22)$$

Case 2)

$$\mathbf{W}_{k+1} = \mathbf{W}_k - \mu_{MED}A_k + \frac{\mu_{MED}}{P_B(k)}B_k , \quad (23)$$

Case 3)

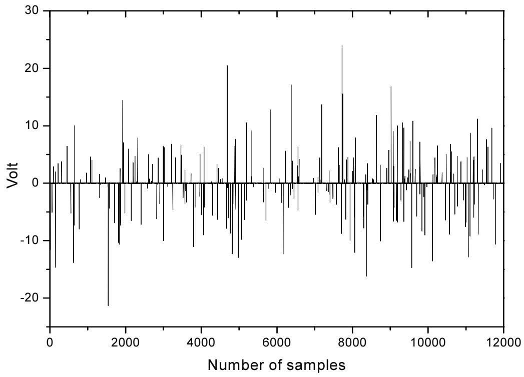
$$\mathbf{W}_{k+1} = \mathbf{W}_k - \frac{\mu_{MED}}{P_A(k)}A_k + \frac{\mu_{MED}}{P_B(k)}B_k . \quad (24)$$

The MED algorithm in (8) is without normalization to A_k nor B_k. Case1 is for observing changes in fluctuation of steady state MSE by normalizing only $\mu_{MED,A}$ compared to MED. Case 2 is to observe whether the normalization of $\mu_{MED,B}$ lowers the steady state MSE of MED without managing A_k . Finally we see if Case 3 employing $\mu_{MED,A}$ and $\mu_{MED,B}$ simultaneously yields both of the two performance enhancements; reduced fluctuation of steady state MSE and lowered steady state MSE.

For the experiment, a base-band communication Casel with impulsive-noise added multipath fading channel is used. One of the equally probable 4 symbols (-3, -1, 1, 3)) is chosen randomly and transmitted. The transmitted symbol is distorted by the multipath channel $H(z) = 0.304 + 0.903z^{-1} + 0.304z^{-2}$ [8]. The channel output is contaminated with impulsive noise n_k and then comes into the equalizer as input. The impulsive noise n_k has the following distribution function $f(n_k)$ where σ_{IN}^2 is the variance of impulses generated according to Poisson process with occurrence rate ε and σ_{GN}^2 is the variance of the background Gaussian noise [9][10].

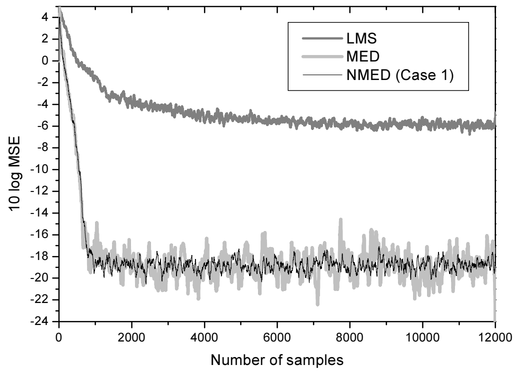
$$f(n_k) = \frac{1-\varepsilon}{\sigma_{GN}\sqrt{2\pi}}\exp[\frac{-n_k^{\ 2}}{2\sigma_{GN}^2}] + \frac{\varepsilon}{\sqrt{2\pi(\sigma_{GN}^2+\sigma_{IN}^2)}}\exp[\frac{-n_k^{\ 2}}{2(\sigma_{GN}^2+\sigma_{IN}^2)}]. \qquad (25)$$

An impulsive noise sample used in this simulation is described in Figure 1 where $\varepsilon = 0.03$, $\sigma_1^2 = \sigma_{GN}^2 = 0.001$ and $\sigma_2^2 = \sigma_{GN}^2 + \sigma_{IN}^2 = 50.001$.

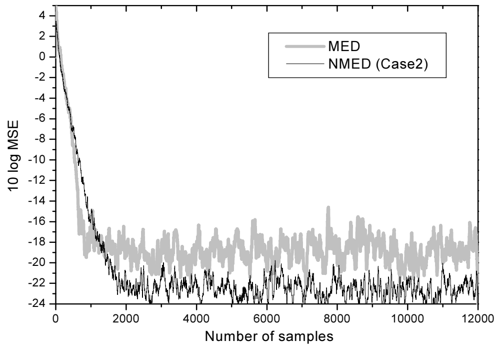


(그림 1) 충격성 잡음과 배경 잡음 AWGN
(Figure 1) The impulse noise and background AWGN.

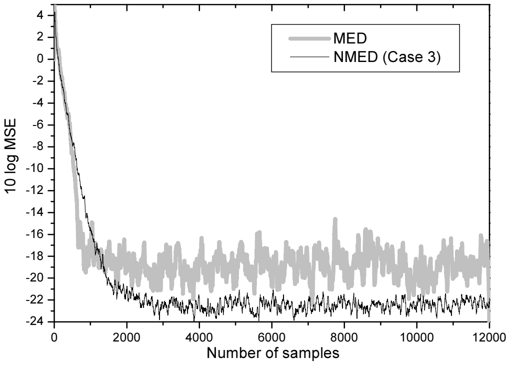
The equalizer has an 11-tap TDL structure and the step size for LMS is $\mu_{LMS} = 0.002$. The MED and the proposed algorithms have common parameters valued the same as $\mu_{MED} = 0.01$, $N = 6$, and $\sigma = 0.8$. Figure 2 shows the MSE learning curves for LMS, MED and Case1 proposed. As discussed in section 2, we observe that the learning curve of LMS does not drop down below -6 dB showing no ability to cope with impulsive noise. On the other hand, the MED type algorithms show rapid and stable convergence. The same speed of convergence between MED and Case 1 is observed but after convergence the Case1 shows smaller fluctuation of steady state MSE than the original MED algorithm verifying the analysis of A_k. Noticing the same steady state MSE, we find that A_k plays the role of pulling error samples close together. In Figure 3 MED and Case 2 are compared and shows that after convergence the Case 2 yields significantly lower steady state MSE than the original MED but has no effect on perturbation in steady state. This indicates that the role of B_k is related with minimum MSE and its power normalization produces improvement of lowering minimum MSE. Furthermore, Case 3 employing $\mu_{MED,A}$ and $\mu_{MED,B}$ simultaneously proves to yield both of the two performance enhancements revealing reduced fluctuation of and lowered steady state MSE as depicted in Figure 4.



(그림 2) A_k 정규화에 대한 MSE 수렴성능
(Figure 2) MSE convergence performance for A_k normalization.



(그림 3) B_k 정규화에 대한 MSE 수렴성능
(Figure 3) MSE convergence performance for B_k normalization .



(그림 4) A_k와 B_k 정규화에 대한 MSE 수렴성능

(Figure 4) MSE convergence performance for A_k and B_k normalization.

6. CONCLUSION

The Euclideandistance between error distribution and Dirac delta function as a performance criterion can be minimized in order to force the distribution of system error to come close to a shape of delta function located at zero. The minimization process uses its gradient, and the gradient has two components; one for kernel function of error-gap value and the other for kernel function of error.

In this paper, we analyze that the first component A_k is to govern minimization of entropy error, that is, gathering close together error samples, and the other component B_k is to take part in maximization of error-sample concentration on zero. Based on this, we propose that normalizing A_k and B_k with power of modified inputs through kernelled entropy errors or errors can improve their roles of reducing error-gap (fluctuation of steady state MSE) and error value (minimum MSE), respectively.

Through simulation in multipath channel equalization under impulsive noise, it is revealed that A_k and B_k has different roles of managing error samples and the proposed method of normalization with power of modified inputs through kernelled error-gap value and error sample can improve learning performance with reducing misadjustment and lowering steady state MSE in impulsive noise environment.

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