Parameter Estimation of Short Duration Data Using Fast Adaptive Algorithm

○ Hirofumi Yogo, Tadashi Kitamura and Naoki Inagaki
*Department of Electrical and Computer Engineering
Nagoya Institute of Technology
Gokiso-cho, Showa-ku, Nagoya 466, Japan*

Abstract A fast and new parameter estimation method is proposed in this paper. The proposed method utilizes the inverse system based on an adaptive digital filter (ADF). As an adaptive algorithm, "Accelerated Stochastic Approximation (ASA)" method is used. The ASA method adopts the time-varying and the optimized convergence factor, and converges within 25 iterations. As the applications of the proposed method, two examples of the parameter estimation of the ARMA model and the natural stop consonants are presented.

1. Introduction

A method of an adaptive signal processing is utilized for a wide variety of applications.[1]-[6] The method is useful for a time-varying signal, specifically varying-signal in a short time. A new parameter estimation method of a short duration data based on adaptive technique is proposed in this paper. As an example of the short duration data, stop consonants were used. Stop consonants are composed of the consonant and the vowel segment, and their intrinsic features exist within the short duration (about 10 mS to 20 mS) between the consonant and the vowel segment. Speech production process of the stop consonant is expressed by an autoregressive and moving-average (ARMA) model. Several intricate procedures have been utilized for the parameter estimation of the ARMA model.[7]-[8] This paper showed that a fast parameter estimation of the short duration data was facilitated by using the method based on an adaptive digital filter (ADF). As an adaptive algorithm of the ADF, a fast adaptive algorithm was developed by improving a conventional stochastic approximation (SA) method [9]. The algorithm was named the Accelerated Stochastic Approximation (ASA) method.[10] The ASA method converges within 25 iterations. When a sampling frequency of 10

kHz is used, only 2.5 mS duration data is needed for the parameter estimation.

As the applications of the proposed method, the parameter estimation of the ARMA model and the stop consonants was performed.

2. Accelerated Stochastic Approximation (ASA) method

The ASA method uses the time-varying and optimized convergence factor with respect to each parameter to be estimated, and is described in Eq.(1).

$$W(j+1) = W(j) + e(j)P(j)^T \mu(j) / (j+h) \quad (1)$$

where

$$W(j) = \text{col} [b_0(j), \dots, b_N(j), a_1(j), \dots, a_M(j)]$$

$$P(j) = \text{col} [\beta_0(j), \dots, \beta_N(j), \alpha_1(j), \dots, \alpha_M(j)]$$

$$\mu(j) = \text{diag} [\mu_{b0}(j), \dots, \mu_{bN}(j), \mu_{a1}(j), \dots, \mu_{aM}(j)]$$

The $\alpha_k(j)$, and $\beta_p(j)$ are the gradient with respect to error $e(j)$, and are given in Eqs. (2) and (3).

$$\alpha_k(j) = -\partial e(j) / \partial a_k(j), \quad k = 1, \dots, M \quad (2)$$

$$\beta_k(j) = -\partial e(j) / \partial b_k(j), \quad k = 0, \dots, N \quad (3)$$

α_k and β_k are given in Eqs.(4) and (5).

$$\alpha_k(j) = y(j-k) + \sum_{i=1}^M a_i(j) \alpha_k(j-i) \quad k = 1, \dots, M \quad (4)$$

$$\beta_k(j) = x(j-k) + \sum_{i=1}^N a_i(j) \beta_k(j-i) \quad k = 0, \dots, N \quad (5)$$

Moreover, $a_k(j)$ and $b_k(j)$ are calculated by Eqs. (6) and (7).

$$a_k(j+1) = a_k(j) + u e(j) \alpha_k(j), \quad k = 1, \dots, M \quad (6)$$

$$b_k(j+1) = b_k(j) + v e(j) \beta_k(j), \quad k = 0, \dots, N \quad (7)$$

$e(j) = d(j) - y(j)$, $d(j)$: disired value
 $y(j)$: output of the ADF, T : transpose,
 $x(j)$: input of the ADF, h : constant,
 j : time index, u, v : constant

Individual convergence factors $\mu_{ak}(j)$ and $\mu_{bp}(j)$ are given in Eqs.(8) and (9).

$$\mu_{ak}(j) = \mu_0 (1 - e^{-\|e(j)x(j)\|}) / (1 + e^{nj}). \quad \mu_{ak}^*(j), \quad k = 1, \dots, M \quad (8)$$

$$\mu_{bp}(j) = \mu_0 (1 - e^{-\|e(j)x(j)\|}) / (1 + e^{nj}). \quad \mu_{bp}^*(j), \quad p = 0, \dots, N \quad (9)$$

The $\mu_{ak}^*(j)$ and $\mu_{bp}^*(j)$ denote the optimized individual convergence factors[11]-[12], and are given in Eqs.(10) and (11).

$$\mu_{ak}^*(j) = 0.5 \alpha \left| \partial e(j) / \partial a_k(j) \right| / \sum_{i=1}^N \{ \partial e(j) / \partial a_i(j) \}^3 \quad (10)$$

$$\mu_{bp}^*(j) = 0.5 (1 - \alpha) \left| \partial e(j) / \partial b_k(j) \right| / \sum_{i=1}^M \{ \partial e(j) / \partial b_i(j) \}^3 \quad (11)$$

where

$\alpha = M + N / (M + N + 1)$, $\mu_0 = 1 / (M + 1) \cdot \sigma^2$
 $\|\cdot\|$: vector norm, σ^2 : input power,
 M, N : model order, n : constant

Fig.1 Block diagram of the inverse system using ADF.

Fig.2 Convergence property of the inverse system.

3. Parameter estimation of the ARMA model

The parameter estimation scheme of the ARMA model with known parameters is shown in Fig.1. $H(z)$ denotes a transfer function of the speech production model, and is given in Eq. (12).

$$H(z) = \frac{(1 + \theta_1 z^{-1} + \dots + \theta_q z^{-q})}{(1 - \Phi_1 z^{-1} - \dots - \Phi_p z^{-p})} \quad (12)$$

where $\Phi_1, \dots, \Phi_p$ denote AR parameters, and $\theta_1, \dots, \theta_q$ MA parameters.

Moreover, $G(z)$ denotes the transfer function of the ADF, and given in Eq. (13).

$$G(z) = \frac{(b_1 + b_2 z^{-1} + \dots + b_p z^{-p+1})}{(1 - a_1 z^{-1} - \dots - a_q z^{-q})} \quad (13)$$

where $a_1, \dots, a_q$ denote AR parameters and $b_1, \dots, b_p$ MA parameters.

The parameters of the ARMA model are obtained by using the inverse system based on ASA method, and by minimizing the estimation errors. The estimated parameters are given in Eqs. (14) and (15).

$$\Phi_k = a_k + b_k \quad k = 1, \dots, p \quad (14)$$

$$\theta_k = -a_k \quad k = 1, \dots, q \quad (15)$$

An example of the convergence characteristics of the ARMA(4,4) model is shown in Fig.2. The AR and the MA parameters are converged less than 25 iterations.

In the next place, impulse responses of both the known and the estimated models are calculated for the comparison of the estimation accuracy. And then, 1024 points FFT transformations of the impulse responses are performed, and the power spectra were obtained. The number of the data derived from the impulse response is small, and zero data was added. The procedure is shown in Fig.3, and the results are shown in Fig.4. Fig.4(a) shows the power spectra based on the estimated parameters, and Fig.4(b) the spectra based on the

known parameters. The estimated spectra have a little degraded characteristics in zero at high frequency. However, we can recognize that the almost similar properties were obtained. Therefore, it is presumed that the reasonable parameter estimations based on the inverse system are performed.

Fig.3 Block diagram of parameter estimation (ARMA model)

4. Analysis of Stop Consonants

As an application of the proposed method, feature extraction of the voiced and the unvoiced stop consonants was performed according to Fig.5. The AR and the MA parameters are estimated from the transitional portion between the consonant and the vowel segment without any particular restrictions. The algorithm utilized converges within 25 iterations, and only needs 2.5 mS duration data. The model order was fixed to 6 because the degraded result was not obtained even though the model orders was selected to larger value than the presumed one.

(a)

(b)

Fig.4 Estimated spectrum (ARMA model)
(a) Proposed method
(b) Conventional FFT method

In the following, the impulse responses of the ARMA model with the estimated parameters were calculated. And the power spectra were obtained by executing 1024 point FFT transformation of the impulse response. The spectra of the unvoiced stop consonants are shown in Fig.6. The above-mentioned procedures were repeated 11 times for the transitional portion by shifting 1 mS with each frame of 2 mS. Fig.6(a) shows the results based on the proposed method, and Fig.6(b) the spectra obtained by a conventional FFT transformation of 25 point real speech data. Moreover, the parameter estimation and the spectra calculation of the voiced stop consonants were performed using

Fig.5 Block diagram of parameter estimation (stop consonant)

the above-mentioned procedures. The spectra of the voiced stop consonants are shown in Fig.7. In the both figures of Fig.6 and Fig.7, the spectra based on the proposed method have the remarkable features.

5. Conclusions

In this paper, we proposed a fast parameter estimation method using the adaptive digital filter (ADF) based on the ASA method. The method is able to estimate the parameters of a short duration data such as 2.5 mS long. As the applications of the proposed method, we presented two examples of the parameter estimation of the ARMA model and the natural stop consonants. The results showed that the proposed method was useful for the parameter estimation of a short duration data. For further study, analysis of other phonemes and the words utilizing this method shall be included. We also intend to accomplish the recognition experiments of the stop consonants using a neural network.

Fig.6 Spectra of the stop consonant (Unvoiced)
(a) Proposed method
(b) Conventional FFT method

Fig.7 Spectra of the stop consonant (Voiced)
(a) Proposed method
(b) Conventional FFT method

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