

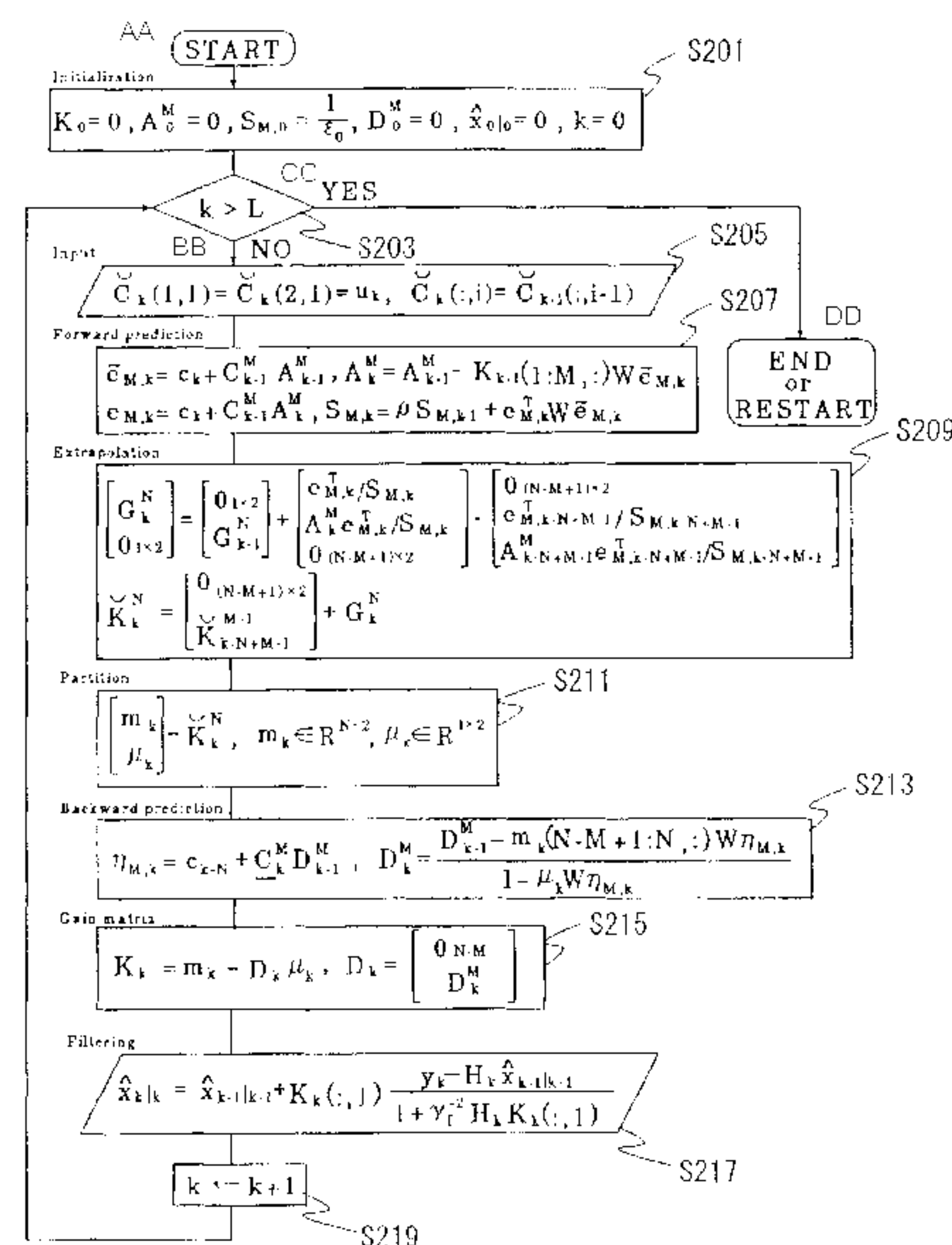


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(54) Titre : PROCEDE ET LOGICIEL D'IDENTIFICATION DE SYSTEME, SUPPORT D'ENREGISTREMENT, ET
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(54) Title: SYSTEM IDENTIFYING METHOD AND PROGRAM, STORAGE MEDIUM, AND SYSTEM IDENTIFYING
DEVICE

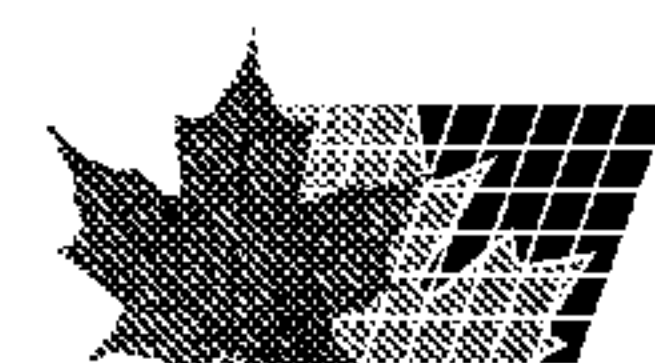


$$C_k^M = \check{C}_k(:, N-M+1:N), C_{k-1}^M = \check{C}_k(:, 2:M+1), H_k = \check{C}_k(1, 1:N).$$

AA DEBUT
S201 INITIALISATION
S205 ENTRÉE
S207 PRÉDICTION DIRECTE
S209 EXTRAPOLATION
S211 DÉCOUPAGE
S213 PRÉDICTION RÉGRESSIVE
S215 MATRICE DE GAIN
S217 FILTRAGE
BB NON
CC OUI
DD FIN OU REDÉMARRAGE

(57) Abrégé/Abstract:

A large-scale sound system or communication system is numerically and stably identified. When an input signal is represented by the $M(\leq N)$ -th order AR model, high-speed H_∞ filtering can be performed with a computational complex $3N + O(M)$. A processing



(57) **Abrégé(suite)/Abstract(continued):**

section determines the initial state of a recursive equation (S201), sets C_k^U according to an input u_k (S205), determines a variable recursively (S207), updates a matrix G_k^N , calculates an auxiliary gain matrix $K_k^{U,N}$ (S209), divides it (S211), calculates a variable D_k^M and a backward prediction error $\eta_{M,k}$ (S213), calculate a gain matrix K_k (S215), and updates a filter equation of a high-speed H_∞ filter (S217). To reduce the computational complexity, $K_k(:, 1)/(1+\gamma_f^{-2} H_k K_k(:, 1))$ is directly used as the filter gain $K_{s,k}$.

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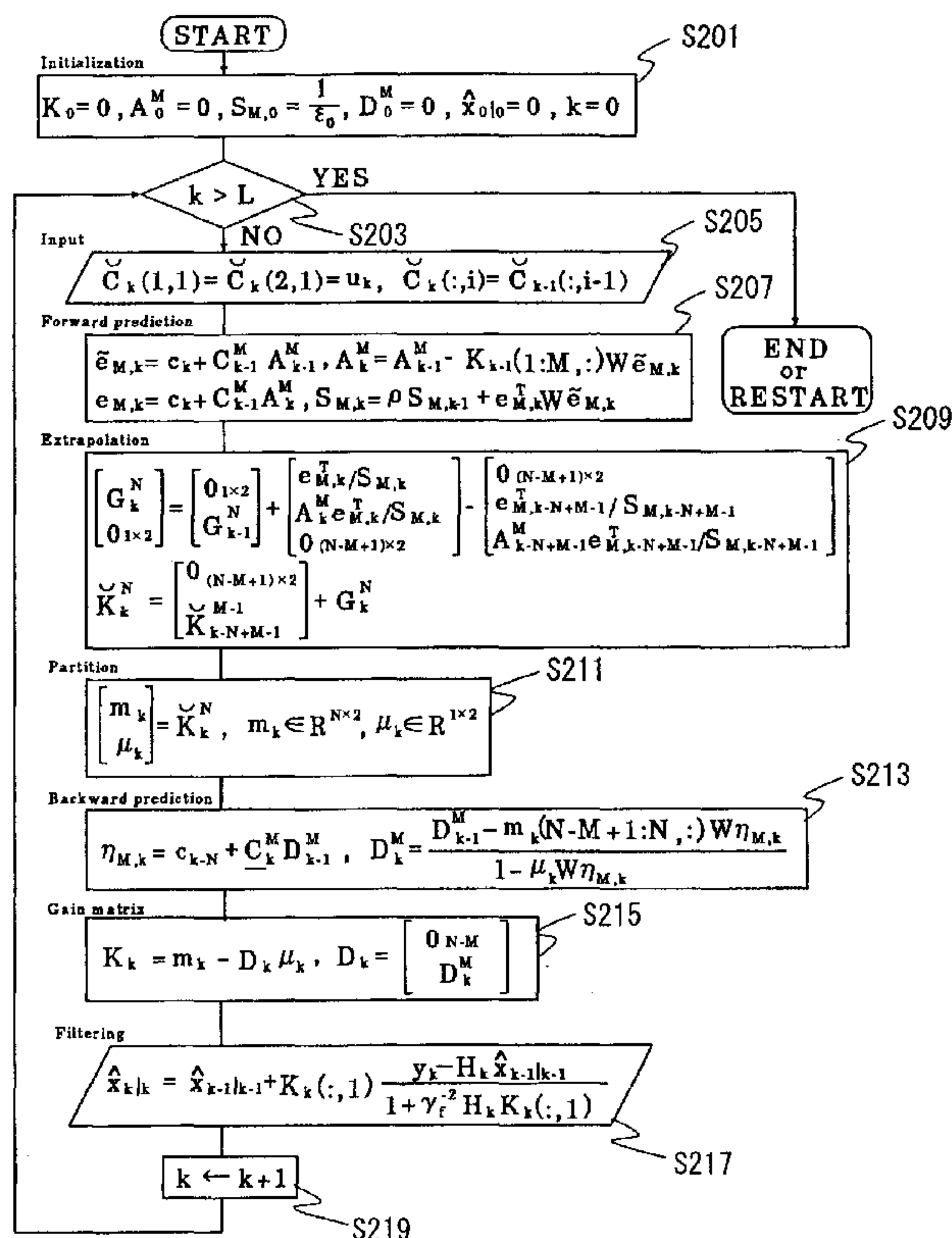
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[続葉有]

(54) Title: SYSTEM IDENTIFYING METHOD AND PROGRAM, STORAGE MEDIUM, AND SYSTEM IDENTIFYING DEVICE

(54) 発明の名称: システム同定方法及びプログラム及び記憶媒体、システム同定装置



$$\underline{C}_k^M = \check{C}_k(:, N-M+1:N), \underline{C}_{k-1}^M = \check{C}_k(:, 2:M+1), H_k = \check{C}_k(1, 1:N).$$

(57) Abstract: A large-scale sound system or communication system is numerically and stably identified. When an input signal is represented by the $M(\leq N)$ -th order AR model, high-speed H_∞ filtering can be performed with a computational complex $3N + O(M)$. A processing section determines the initial state of a recursive equation (S201), sets $\underline{C}_k^U$ according to an input u_k (S205), determines a variable recursively (S207), updates a matrix G_k^N , calculates an auxiliary gain matrix K_k^{UN} (S209), divides it (S211), calculates a variable D_k^M and a backward prediction error $\eta_{M,k}$ (S213), calculate a gain matrix K_k (S215), and updates a filter equation of a high-speed H_∞ filter (S217). To reduce the computational complexity, $K_k(:, 1)/(1 + \gamma_f^{-2} H_k K_k(:, 1))$ is directly used as the filter gain $K_{s,k}$.

(57) 要約: 大規模な音響系または通信系を高速かつ数値的に安定に同定する。高速 H_∞ フィルタ処理では、入力信号が $M(\leq N)$ 次の AR モデルで表されるとき、計算量 $3N + O(M)$ で実行できる。処理部は、再帰式の初期状態を定め (S201)、入力 u_k に従い $\underline{C}_k^U$ を設定し (S205)、変数を再帰的に決定する (S207)。処理部は、行列 G_k^N を更新し、補助ゲイン行列 K_k^{UN} を計算し (S209)、分割する (S211)。処理部は、変数 D_k^M 及び後方予測誤差 $\eta_{M,k}$ を計算し (S213)、ゲイン行列 K_k を計算する (S215)。処理部は、高速 H_∞ フィルタのフィルタ方程式を更新する (S217)。ここで、計算量削減のため、フィルタゲイン $K_{s,k}$ として $K_k(:, 1) / (1 + \gamma_f^{-2} H_k K_k(:, 1))$ を直接用いている。

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SYSTEM IDENTIFICATION METHOD AND PROGRAM, STORAGE MEDIUM, AND
SYSTEM IDENTIFICATION DEVICE

Technical Field

5

[0001]

The present invention relates to a system identification method and program, a storage medium, and a system identification device, and particularly to a numerically
10 stabilized fast identification method. Besides, the present invention relates to various system identification methods such as fast identification of a large-scale sound system or communication system using characteristics of a sound as an input signal.

15

Background Art

[0002]

System identification means estimating a mathematical
20 model (transfer function, impulse response, etc.) of an input/output relation of a system based on input/output data, and typical application examples include an echo canceller in international communication, an automatic equalizer in data communication, an echo canceller and sound field reproduction
25 in a sound system, active noise control in a vehicle etc. and the like. Hitherto, as an adaptable algorithm in the system identification, LMS (Least Mean Square), RLS (Recursive Least Square), or Kalman filter is widely used. In general, an observed value of output of a system is expressed as follows:

30 [Mathematical Expression 1]

$$y_k = \sum_{i=0}^{N-1} h_i u_{k-i} + v_k \quad (1)$$

Where, u_k denotes an input, h_i denotes an impulse response of the system, and v_k is assumed to be a white noise.

The details are described in non-patent document 1 or
5 the like.

[0003]

1. LMS

In the LMS, an impulse response $x_k = [h_0, \dots, h_{N-1}]^T$ of
10 a system is estimated from an input u_k and an output y_k as follows:

[Mathematical Expression 2]

$$\hat{x}_k = \hat{x}_{k-1} + \mu H_k^T (y_k - H_k \hat{x}_{k-1}) \quad (2)$$

Where, $H_k = [u_k, \dots, u_{k-N+1}]^T$, $\mu > 0$.

15

[0004]

2. RLS

In the RLS, an impulse response $x_k = [h_0, \dots, h_{N-1}]^T$ of
a system is estimated from an input u_k and an output y_k as
20 follows:

[Mathematical Expression 3]

$$\hat{x}_k = \hat{x}_{k-1} + K_k (y_k - H_k \hat{x}_{k-1}) \quad (3)$$

$$K_k = \frac{P_{k-1} H_k^T}{\rho + H_k P_{k-1} H_k^T} \quad (4)$$

$$P_k = (P_{k-1} - K_k H_k P_{k-1}) / \rho \quad (5)$$

Where, $\hat{x}_0 = 0$, $P_0 = \varepsilon_0 I$, $\varepsilon_0 > 0$, 0 denotes a zero vector, I denotes
a unit matrix, K_h denotes a filter gain, and ρ denotes a
25 forgetting factor. (Incidentally, " $\hat{}$ ", " $\hat{}$ " means an estimated
value and should be placed directly above a character as
represented by the mathematical expressions. However, it is

placed at the upper right of the character for input convenience.
The same applies hereinafter.)

[0005]

5 3. Kalman filter

A minimum variance estimate $\hat{x}_{k|k}$ of a state x_k of a linear system expressed in a state space model as indicated by [Mathematical Expression 4]

$$x_{k+1} = \rho^{-\frac{1}{2}} x_k, \quad y_k = H_k x_k + v_k \quad (6)$$

10 is obtained by a following Kalman filter.

[Mathematical Expression 5]

$$\begin{aligned} \hat{x}_{k|k} &= \hat{x}_{k|k-1} + K_k (y_k - H_k \hat{x}_{k|k-1}) \\ \hat{x}_{k+1|k} &= \rho^{-\frac{1}{2}} \hat{x}_{k|k} \end{aligned} \quad (7)$$

$$K_k = \hat{\Sigma}_{k|k-1} H_k^T (\rho + H_k \hat{\Sigma}_{k|k-1} H_k^T)^{-1} \quad (8)$$

$$\begin{aligned} \hat{\Sigma}_{k|k} &= \hat{\Sigma}_{k|k-1} - K_k H_k \hat{\Sigma}_{k|k-1} \\ \hat{\Sigma}_{k+1|k} &= \hat{\Sigma}_{k|k} / \rho \end{aligned} \quad (9)$$

Where,

[Mathematical Expression 6]

$$15 \quad \hat{x}_{1|0} = 0, \quad \hat{\Sigma}_{1|0} = \varepsilon_0 I, \quad \varepsilon_0 > 0 \quad (10)$$

x_k : a state vector or simply a state; unknown, and this is an object of estimation.

y_k : an observation signal; an input of the filter and known.

H_k : an observation matrix; known.

20 v_k : an observation noise; unknown.

ρ : a forgetting factor; generally determined by trial and error.

K_k : a filter gain; obtained from a matrix $\hat{\Sigma}_{k|k-1}$.

$\hat{\Sigma}_{k|k}$: corresponding to a covariance matrix of an error of $\hat{x}_{k|k}$;

obtained by a Riccati equation.

$\Sigma_{k+1|k}^{\wedge}$: corresponding to a covariance matrix of an error of $\hat{x}_{k+1|k}$; obtained by a Riccati equation.

$\Sigma_{1|0}^{\wedge}$: corresponding to a covariance matrix of an initial state;

5 although unknown, ϵ_0^1 is used for convenience.

[0006]

In addition, hitherto, there are techniques described in patent documents 1 and 2 and non-patent documents 2 to 5.

Patent document 1: WO 02/035727, JP-A-2002-135171

10 Patent document 2: WO 2005/015737

Non-patent document 1: S. Haykin, Adaptive Filter Theory, 3rd Edition, Prentice-Hall, 1996

Non-patent document 2: K. Nishiyama, Derivation of a Fast Algorithm of Modified H_{∞} Filters, Proceedings of IEEE International Conference on Industrial Electronics, Control and Instrumentation, RBC-II, pp. 462-467, 2000

Non-patent document 3: K. Nishiyama, An H_{∞} Optimization and Its Algorithm for Time-Variant System Identification, IEEE Transactions on Signal Processing, 52, 5, pp.1335-1342, 2004

20 Non-patent document 4: B. Hassibi, A.H. Sayed, and T. Kailath, Indefinite-Quadratic Estimation and Control, 1st Editions, SIAM, 1999

Non-patent document 5: G. Glentis, K. Berberidis, and S. Theodoridis, Efficient least squares adaptive algorithms for FIR transversal filtering, IEEE Signal Processing Magazine, 16,4, pp.13-41, 1999

Disclosure of the Invention

Problems that the Invention is to Solve

[0007]

At present, an adaptive algorithm most widely used in the system identification is the LMS. The LMS has a problem that although the amount of calculation is small, convergence speed is very low. On the other hand, in the RLS or the Kalman filter, the value of the forgetting factor ρ which dominates the tracking performance must be determined by trial and error, and this is generally a very difficult work. Further, there is no means for determining whether the determined value of the forgetting factor is really an optimum value.

Besides, although $\sum_{k=1}^N$ or P_k is originally a positive-definite matrix, in the case where calculation is performed at single precision (example: 32 bit), it often becomes negative definite, and this is one of factors to make the Kalman filter or the RLS numerically unstable. Besides, since the amount of calculation is $O(N^2)$, when the dimension (tap number) of a state vector x_k is large, the number of times of arithmetic operation per step is rapidly increased, and there has been a case where it is not suitable for a real-time processing.

In view of the above, the present invention has an object to provide an identification method for identifying a large-scale sound system or communication system at high speed and numerically stably. Besides, the invention has an object to derive an algorithm to greatly reduce the amount of calculation of a previously proposed fast H_∞ filter by using characteristics of a sound as an input signal. Further, the invention has an object to provide a method of numerically stabilizing a fast H_∞ filter by using a backward prediction error.

Means for Solving the Problems

[0008]

5 According to the first solving means of this invention, there is provided a system identification device for performing fast real-time identification of a time invariable or time variable system, comprising:

10 a filter that is robust against a disturbance by determining that a maximum energy gain to a filter error from the disturbance, as an evaluation criterion, is restricted to be smaller than a previously given upper limit γ_f^2 ,

wherein

15 the filter satisfies an H_∞ evaluation criterion as indicated by following expression (14) with respect to a state space model as indicated by following expressions (11) to (13),

when an input signal is expressed by an $M(\leq N)$ -th order autoregressive model (AR model), the filter is given by following expressions (38) to (44), and

20 the filter satisfies a scalar existence condition of following expressions (45) and (46):

[Mathematical Expression 1]

$$\mathbf{x}_{k+1} = \mathbf{x}_k + \mathbf{G}_k \mathbf{w}_k, \quad \mathbf{w}_k, \mathbf{x}_k \in \mathcal{R}^N \quad (11)$$

$$y_k = \mathbf{H}_k \mathbf{x}_k + v_k, \quad y_k, v_k \in \mathcal{R} \quad (12)$$

$$z_k = \mathbf{H}_k \mathbf{x}_k, \quad z_k \in \mathcal{R}, \mathbf{H}_k \in \mathcal{R}^{1 \times N} \quad (13)$$

$$\sup_{x_0, \{w_i\}, \{v_i\}} \frac{\sum_{i=0}^k \|e_{f,i}\|^2 / \rho}{\|\mathbf{x}_0 - \tilde{\mathbf{x}}_0\|_{\Sigma_0^{-1}}^2 + \sum_{i=0}^k \|\mathbf{w}_i\|^2 + \sum_{i=0}^k \|v_i\|^2 / \rho} < \gamma_f^2 \quad (14)$$

25 [Mathematical Expression 2]

$$\hat{\mathbf{x}}_{k|k} = \hat{\mathbf{x}}_{k-1|k-1} + \mathbf{K}_{s,k}(y_k - \mathbf{H}_k \hat{\mathbf{x}}_{k-1|k-1}) \quad (38)$$

$$\mathbf{K}_{s,k} = \frac{\mathbf{K}_k(:, 1)}{1 + \gamma_f^{-2} \mathbf{H}_k \mathbf{K}_k(:, 1)} \in \mathcal{R}^{N \times 1}$$

$$\mathbf{K}_k = \mathbf{m}_k - \mathbf{D}_k \boldsymbol{\mu}_k, \quad \mathbf{D}_k = \begin{bmatrix} \mathbf{0}_{N-M} \\ \mathbf{D}_k^M \end{bmatrix} \quad (39)$$

$$\mathbf{D}_k^M = \frac{\mathbf{D}_{k-1}^M - \mathbf{m}_k(N-M+1:N, :) \mathbf{W} \boldsymbol{\eta}_{M,k}}{1 - \boldsymbol{\mu}_k \mathbf{W} \boldsymbol{\eta}_{M,k}}$$

$$\boldsymbol{\eta}_{M,k} = \mathbf{c}_{k-N} + \mathbf{C}_k^M \mathbf{D}_{k-1}^M \quad (40)$$

$$\begin{bmatrix} \mathbf{m}_k \\ \boldsymbol{\mu}_k \end{bmatrix} = \check{\mathbf{K}}_k^N, \quad \mathbf{m}_k \in \mathcal{R}^{N \times 2}, \quad \boldsymbol{\mu}_k \in \mathcal{R}^{1 \times 2} \quad (41)$$

$$\check{\mathbf{K}}_k^N = \begin{bmatrix} \mathbf{0}_{(N-M+1) \times 2} \\ \check{\mathbf{K}}_{k-N+M-1}^{M-1} \end{bmatrix} + \mathbf{G}_k^N, \quad \check{\mathbf{K}}_{k-N+M-1}^{M-1} = \mathbf{K}_{k-N+M-1}(1:M, :) \quad (42)$$

$$\begin{aligned} S_{M,k} &= \rho S_{M,k-1} + \mathbf{e}_{M,k}^T \mathbf{W} \tilde{\mathbf{e}}_{M,k}, \quad \mathbf{e}_{M,k} = \mathbf{c}_k + \mathbf{C}_{k-1}^M \mathbf{A}_k^M \\ \mathbf{A}_k^M &= \mathbf{A}_{k-1}^M - \mathbf{K}_{k-1}(1:M, :) \mathbf{W} \tilde{\mathbf{e}}_{M,k}, \quad \tilde{\mathbf{e}}_{M,k} = \mathbf{c}_k + \mathbf{C}_{k-1}^M \mathbf{A}_{k-1}^M \end{aligned} \quad (43)$$

here, $\mathbf{G}_k^N$ is updated as follows:

$$\begin{aligned} \begin{bmatrix} \mathbf{G}_k^N \\ \mathbf{0}_{1 \times 2} \end{bmatrix} &= \begin{bmatrix} \mathbf{0}_{1 \times 2} \\ \mathbf{G}_{k-1}^N \end{bmatrix} + \begin{bmatrix} \mathbf{e}_{M,k}^T / S_{M,k} \\ \mathbf{A}_k^M \mathbf{e}_{M,k}^T / S_{M,k} \\ \mathbf{0}_{(N-M+1) \times 2} \end{bmatrix} \\ &\quad - \begin{bmatrix} \mathbf{0}_{(N-M+1) \times 2} \\ \mathbf{e}_{M,k-N+M-1}^T / S_{M,k-N+M-1} \\ \mathbf{A}_{k-N+M-1}^M \mathbf{e}_{M,k-N+M-1}^T / S_{M,k-N+M-1} \end{bmatrix} \end{aligned} \quad (44)$$

where,

$$\mathbf{C}_k(:, N-M+1:N), \mathbf{C}_{k-1}^M = \mathbf{C}_{k-1}(:, 1:M), \quad \mathbf{C}_k = \begin{bmatrix} \mathbf{H}_k \\ \mathbf{H}_k \end{bmatrix}, \quad \mathbf{W} = \begin{bmatrix} 1 & 0 \\ 0 & -\gamma_f^{-2} \end{bmatrix}$$

5

$$\mathbf{e}_{f,i} = \mathbf{z}_{i|i}^v - \mathbf{H}_i \mathbf{x}_i, \quad \mathbf{z}_{i|i}^v = \mathbf{H}_i \hat{\mathbf{x}}_{i|i}$$

($\mathbf{c}_k \in \mathcal{R}^{2 \times 1}$ is a first column vector of $\mathbf{C}_k = [\mathbf{c}_k, \dots, \mathbf{c}_{k-N+1}]$,
 $\mathbf{c}_{k-1} = \mathbf{0}_{2 \times 1}$ and $k-i < 0$ are assumed, and initial values are set
to be $\mathbf{K}_0 = \mathbf{0}_{N \times 2}$, $\mathbf{G}_0^N = \mathbf{0}_{(N+1) \times 2}$, $\mathbf{A}_0^M = \mathbf{0}_{M \times 1}$, $S_{M,0} = 1/\varepsilon_0$, $\mathbf{D}_0^M = \mathbf{0}_{M \times 1}$,

10 $\hat{\mathbf{x}}_{0|0} = \mathbf{x}^v_0 = \mathbf{0}_{N \times 1}$, here, $\mathbf{0}_{m \times n}$ denotes an $m \times n$ zero matrix)

[Mathematical Expression 3]

$$-\varrho \hat{\Xi}_i + \rho \gamma_f^2 > 0, \quad i = 0, \dots, k \quad (45)$$

here, $\varrho, \hat{\Xi}_i$ are respectively defined by following expressions:

$$\varrho = 1 - \gamma_f^2, \quad \hat{\Xi}_i = \frac{\rho \mathbf{H}_i \mathbf{K}_{s,i}}{1 - \mathbf{H}_i \mathbf{K}_{s,i}} = \frac{\rho \mathbf{H}_i \mathbf{K}_i(:, 1)}{1 - (1 - \gamma_f^{-2}) \mathbf{H}_i \mathbf{K}_i(:, 1)} \quad (46)$$

where

$\mathbf{x}_k$: a state vector or simply a state; unknown, this is an object of estimation,

5 $\mathbf{x}_0$: an initial state; unknown,

$\mathbf{w}_k$: a system noise; unknown,

$\mathbf{v}_k$: an observation noise; unknown,

$\mathbf{y}_k$: an observation signal; input of the filter and known,

$\mathbf{z}_k$: an output signal, unknown,

10 $\mathbf{G}_k$: a drive matrix; becomes known at execution,

$\mathbf{H}_k$: an observation matrix; known,

$\hat{\mathbf{x}}_{k|k}$: an estimated value of the state $\mathbf{x}_k$ at a time k using observation signals $\mathbf{y}_0 - \mathbf{y}_k$; given by a filter equation,

$\mathbf{K}_{s,k}$: a filter gain; obtained from a gain matrix $\mathbf{K}_k$,

15 ρ : a forgetting factor; in a case of Theorem 1 - Theorem 3, when γ_f is determined, it is automatically determined by $\rho = 1 - \chi(\gamma_f)$,

Σ_0^{-1} : an inverse matrix of a weighting matrix expressing uncertainty of a state; Σ_0 is known,

20 N : a dimension (tap number) of a state vector; previously given,

M : an order of an AR model; previously given,

μ_k : $N+1$ th row vector of $\mathbf{K}_k^{U,N}$; obtained from $\mathbf{K}_k^{U,N}$,

$\mathbf{m}_k$: $N \times 2$ matrix including a first to an N -th row of $\mathbf{K}_k^{U,N}$; obtained from $\mathbf{K}_k^{U,N}$,

25 γ_f : attenuation level; given at design time

$\mathbf{D}_k^M$: a backward prediction coefficient vector; obtained from $\mathbf{m}_k$, $\eta_{M,k}$ and μ_k ,

$\mathbf{W}$: a weighting matrix; determined from γ_f ,

$\mathbf{A}_k^M$: a forward prediction coefficient vector; obtained from $\mathbf{K}_{k-1}$

and $\tilde{e}_{M,k}$,

C_k^M : a $2 \times M$ matrix including a 1st to an M -th column vector of C_k ; determined from the observation matrix H_k , and

5 $\underline{C}_k^M$: a $2 \times M$ matrix including an $N-M+1$ -th to an N -th column vector of C_k ; determined from the observation matrix H_k .

[0009]

According to the second solving means of this invention, there is provided a system identification method for performing fast real-time identification of a time invariable or time
10 variable system, a system identification program that causes a computer to perform the identification and a computer readable recording medium recording the program, by using:

a filter that is robust against a disturbance by determining that a maximum energy gain to a filter error from
15 the disturbance, as an evaluation criterion, is restricted to be smaller than a previously given upper limit γ_f^2 ,

wherein

the filter satisfies an H_∞ evaluation criterion as indicated by following expression (14) with respect to a state
20 space model as indicated by following expressions (11) to (13),

when an input signal is expressed by an $M(\leq N)$ -th order autoregressive model (AR model), the filter is given by following expressions (38) to (44), and

the filter satisfies a scalar existence condition of
25 following expressions (45) and (46):

[Mathematical Expression 1]

$$\mathbf{x}_{k+1} = \mathbf{x}_k + \mathbf{G}_k \mathbf{w}_k, \quad \mathbf{w}_k, \mathbf{x}_k \in \mathcal{R}^N \quad (11)$$

$$y_k = \mathbf{H}_k \mathbf{x}_k + v_k, \quad y_k, v_k \in \mathcal{R} \quad (12)$$

$$z_k = \mathbf{H}_k \mathbf{x}_k, \quad z_k \in \mathcal{R}, \mathbf{H}_k \in \mathcal{R}^{1 \times N} \quad (13)$$

$$\sup_{x_0, \{w_i\}, \{v_i\}} \frac{\sum_{i=0}^k \|e_{f,i}\|^2 / \rho}{\|x_0 - \check{x}_0\|_{\Sigma_0^{-1}}^2 + \sum_{i=0}^k \|w_i\|^2 + \sum_{i=0}^k \|v_i\|^2 / \rho} < \gamma_f^2 \quad (14)$$

[Mathematical Expression 2]

$$\hat{x}_{k|k} = \hat{x}_{k-1|k-1} + K_{s,k}(y_k - H_k \hat{x}_{k-1|k-1}) \quad (38)$$

$$K_{s,k} = \frac{K_k(:, 1)}{1 + \gamma_f^{-2} H_k K_k(:, 1)} \in \mathcal{R}^{N \times 1}$$

$$K_k = m_k - D_k \mu_k, \quad D_k = \begin{bmatrix} 0_{N-M} \\ D_k^M \end{bmatrix} \quad (39)$$

$$D_k^M = \frac{D_{k-1}^M - m_k(N-M+1:N,:) W \eta_{M,k}}{1 - \mu_k W \eta_{M,k}}$$

$$\eta_{M,k} = c_{k-N} + C_k^M D_{k-1}^M \quad (40)$$

$$\begin{bmatrix} m_k \\ \mu_k \end{bmatrix} = \check{K}_k^N, \quad m_k \in \mathcal{R}^{N \times 2}, \quad \mu_k \in \mathcal{R}^{1 \times 2} \quad (41)$$

$$\check{K}_k^N = \begin{bmatrix} 0_{(N-M+1) \times 2} \\ \check{K}_{k-N+M-1}^{M-1} \end{bmatrix} + G_k^N, \quad \check{K}_{k-N+M-1}^{M-1} = K_{k-N+M-1}(1:M,:) \quad (42)$$

$$S_{M,k} = \rho S_{M,k-1} + e_{M,k}^T W \tilde{e}_{M,k}, \quad e_{M,k} = c_k + C_{k-1}^M A_k^M \\ A_k^M = A_{k-1}^M - K_{k-1}(1:M,:) W \tilde{e}_{M,k}, \quad \tilde{e}_{M,k} = c_k + C_{k-1}^M A_{k-1}^M \quad (43)$$

here, G_k^N is updated as follows:

$$\begin{bmatrix} G_k^N \\ 0_{1 \times 2} \end{bmatrix} = \begin{bmatrix} 0_{1 \times 2} \\ G_{k-1}^N \end{bmatrix} + \begin{bmatrix} e_{M,k}^T / S_{M,k} \\ A_k^M e_{M,k}^T / S_{M,k} \\ 0_{(N-M+1) \times 2} \end{bmatrix} \\ - \begin{bmatrix} 0_{(N-M+1) \times 2} \\ e_{M,k-N+M-1}^T / S_{M,k-N+M-1} \\ A_{k-N+M-1}^M e_{M,k-N+M-1}^T / S_{M,k-N+M-1} \end{bmatrix} \quad (44)$$

5

where,

$$C_k(:, N-M+1:N), C_{k-1}^M = C_{k-1}(:, 1:M), \quad C_k = \begin{bmatrix} H_k \\ H_k \end{bmatrix}, \quad W = \begin{bmatrix} 1 & 0 \\ 0 & -\gamma_f^{-2} \end{bmatrix}$$

$$e_{f,i} = z_{i|i}^v - H_i x_i, \quad z_{i|i}^v = H_i \hat{x}_{i|i}$$

($c_k \in \mathcal{R}^{2 \times 1}$ is a first column vector of $C_k = [c_k, \dots, c_{k-N+1}]$,

10 $c_{k-1} = 0_{2 \times 1}$ and $k-i < 0$ are assumed, and initial values are set

to be $K_0 = 0_{N \times 2}$, $G_0^N = 0_{(N+1) \times 2}$, $A_0^M = 0_{M \times 1}$, $S_{M,0} = 1/\epsilon_0$, $D_0^M = 0_{M \times 1}$,

$\hat{x}_{0|0} = x^v_0 = 0_{N \times 1}$, here, $0_{m \times n}$ denotes an $m \times n$ zero matrix)

[Mathematical Expression 3]

$$-\varrho \hat{\Xi}_i + \rho \gamma_f^2 > 0, \quad i = 0, \dots, k \quad (45)$$

here, $\varrho, \hat{\Xi}_i$ are respectively defined by following expressions:

$$\varrho = 1 - \gamma_f^2, \quad \hat{\Xi}_i = \frac{\rho \mathbf{H}_i \mathbf{K}_{s,i}}{1 - \mathbf{H}_i \mathbf{K}_{s,i}} = \frac{\rho \mathbf{H}_i \mathbf{K}_i(:, 1)}{1 - (1 - \gamma_f^{-2}) \mathbf{H}_i \mathbf{K}_i(:, 1)} \quad (46)$$

where

- 5 $\mathbf{x}_k$: a state vector or simply a state; unknown, this is an object of estimation,
- $\mathbf{x}_0$: an initial state; unknown,
- $\mathbf{w}_k$: a system noise; unknown,
- $\mathbf{v}_k$: an observation noise; unknown,
- 10 $\mathbf{y}_k$: an observation signal; input of the filter and known,
- $\mathbf{z}_k$: an output signal, unknown,
- $\mathbf{G}_k$: a drive matrix; becomes known at execution,
- $\mathbf{H}_k$: an observation matrix; known,
- $\hat{\mathbf{x}}_{k|k}$: an estimated value of the state $\mathbf{x}_k$ at a time k using
- 15 observation signals $\mathbf{y}_0 - \mathbf{y}_k$; given by a filter equation,
- $\mathbf{K}_{s,k}$: a filter gain; obtained from a gain matrix $\mathbf{K}_k$,
- ρ : a forgetting factor; in a case of Theorem 1 - Theorem 3, when γ_f is determined, it is automatically determined by $\rho = 1 - \chi(\gamma_f)$,
- 20 Σ_0^{-1} : an inverse matrix of a weighting matrix expressing uncertainty of a state; Σ_0 is known,
- N : a dimension (tap number) of a state vector; previously given,
- M : an order of an AR model; previously given,
- μ_k : $N+1$ th row vector of $\mathbf{K}_k^{U N}$; obtained from $\mathbf{K}_k^{U N}$,
- 25 $\mathbf{m}_k$: $N \times 2$ matrix including a first to an N -th row of $\mathbf{K}_k^{U N}$; obtained from $\mathbf{K}_k^{U N}$,
- γ_f : attenuation level; given at design time
- $\mathbf{D}_k^M$: a backward prediction coefficient vector; obtained from

m_k , $\eta_{M,k}$ and μ_k ,

W : a weighting matrix; determined from γ_f ,

A_k^M : a forward prediction coefficient vector; obtained from K_{k-1} and $e_{M,k}^{\sim}$,

5 C_k^M : a $2 \times M$ matrix including a 1st to an M -th column vector of C_k ; determined from the observation matrix H_k , and

$\underline{C}_k^M$: a $2 \times M$ matrix including an $N-M+1$ -th to an N -th column vector of C_k ; determined from the observation matrix H_k .

[0010]

10 According to the present invention, it is possible to provide an identification method for identifying a large-scale sound system or communication system at high speed and numerically stably. Besides, according to the present invention, it is possible to derive an algorithm to greatly
15 reduce the amount of calculation of a previously proposed fast H_∞ filter by using characteristics of a sound as an input signal. Further, according to the present invention, it is possible to provide a method of numerically stabilizing a fast H_∞ filter by using a backward prediction error.

20

Brief Description of the Drawings

[0011]

[FIG. 1] An explanatory view showing update of a gain matrix
25 of an order-recursive fast H_∞ filter.

[FIG. 2] A flowchart of a processing of the order-recursive fast H_∞ filter.

[FIG. 3] A flowchart of a check of a scalar existence condition.

30 [FIG. 4] A flowchart of a calculation processing of a value

of a prediction variable at a time $t_{k-N+M-1}$.

[FIG. 5] A flowchart of a numerically stabilized fast H_∞ filter processing.

[FIG. 6] An explanatory view of a communication system and
5 an echo.

[FIG. 7] A principle view of an echo canceller.

[FIG. 8] A view showing an estimation result (performance evaluation) of an impulse response by the order-recursive fast H_∞ filter.

10 [FIG. 9] A convergence characteristic view of the order-recursive fast H_∞ filter with respect to a sound input.

[FIG. 10] A view of comparison of an existence condition.

[FIG. 11] A structural view of hardware of an embodiment.

[FIG. 12] A view of a result of comparison between the amount
15 of calculation of a fast H_∞ filter and that of the order-recursive fast H_∞ filter.

[FIG. 13] A view showing an impulse response of an echo path.

Best Mode for Carrying Out the Invention

20

[0012]

1. Explanation of symbols

First, main symbols used in the embodiment will be described.

25 x_k : a state vector or simply a state; unknown, this is an object of estimation,

x_0 : an initial state; unknown,

w_k : a system noise; unknown,

v_k : an observation noise; unknown,

30 y_k : an observation signal; input of the filter and known,

- z_k : an output signal, unknown,
 G_k : a drive matrix; becomes known at execution,
 H_k : an observation matrix; known,
 $\hat{x}_{k|k}$: an estimated value of the state x_k at a time k using
5 observation signals $y_0 - y_k$; given by a filter equation,
 $K_{s,k}$: a filter gain; obtained from a gain matrix K_k ,
 ρ : a forgetting factor; in a case of Theorem 1 - Theorem 3,
when γ_f is determined, it is automatically determined by $\rho =$
 $1 - \chi(\gamma_f)$,
10 Σ_0^{-1} : an inverse matrix of a weighting matrix expressing
uncertainty of a state; Σ_0 is known,
 N : a dimension (tap number) of a state vector; previously given,
 M : an order of an AR model; previously given,
 μ_k : $N+1$ th row vector of $K_k^{U N}$; obtained from $K_k^{U N}$,
15 m_k : $N \times 2$ matrix including a first to an N -th row of $K_k^{U N}$; obtained
from $K_k^{U N}$,
 γ_f : attenuation level; given at design time
 D_k^M : a backward prediction coefficient vector; obtained from
 m_k , $\eta_{M,k}$ and μ_k ,
20 W : a weighting matrix; determined from γ_f ,
 A_k^M : a forward prediction coefficient vector; obtained from K_{k-1}
and $\tilde{e}_{M,k}$,
 C_k^M : a $2 \times M$ matrix including a 1st to an M -th column vector of
 C_k ; determined from the observation matrix H_k , and
25 $\underline{C}_k^M$: a $2 \times M$ matrix including an $N-M+1$ -th to an N -th column vector
of C_k ; determined from the observation matrix H_k .

Incidentally, " $\wedge$ ", " $\vee$ " placed above the symbol mean
estimated values. Besides, " $\sim$ ", " $-$ ", " U " and the like are
30 symbols added for convenience. Although these symbols are

placed at the upper right of characters for input convenience,
 as indicated in mathematical expressions, they are the same
 as those placed directly above the characters. Besides, x ,
 w , H , G , K , R , Σ and the like are matrixes and should be expressed
 5 by thick letters as indicated in the mathematical expressions,
 however, they are expressed in normal letters for input
 convenience.

[0013]

10 2. Hardware of system estimation and program

A system estimation method or a system estimation
 device/system can be provided by a system estimation program
 to cause a computer to execute respective procedures, a
 computer readable recording medium recording the system
 15 estimation program, a program product including the system
 estimation program and capable of being loaded in an internal
 memory of a computer, a computer, such as a server, including
 the program, and the like.

FIG. 11 is a structural view of hardware of this
 20 embodiment.

The hardware includes a processing section 101 as a
 central processing unit (CPU), an input section 102, an output
 section 103, a display section 104, and a storage section 105.
 Besides, the processing section 101, the input section 102,
 25 the output section 103, the display section 104, and the storage
 section 105 are connected through suitable connection means
 such as a star or a bus. The known data described in "1.
 Explanation of Symbols" and subjected to the system estimation
 are stored in the storage section 105 as the need arises.
 30 Besides, the unknown and known data, calculated data relating

to the hyper H_∞ filter, and the other data are written and/or read by the processing section 101 as the need arises.

[0014]

5 3. Means of an identification method relevant to the embodiment

In order to differentiate from a normal H_∞ filter, an H_∞ filter in which a forgetting factor can be optimally (quasi-optimally) determined in the meaning of H_∞ is especially
10 called a hyper H_∞ filter (non-patent document 2, non-patent document 3). The H_∞ filter has a feature that it can be applied even when the dynamics of a state is unknown.

[0015]

Theorem 1 (hyper H_∞ filter)

15 With respect to a state space model

[Mathematical Expression 13]

$$\mathbf{x}_{k+1} = \mathbf{x}_k + \mathbf{G}_k \mathbf{w}_k, \quad \mathbf{w}_k, \mathbf{x}_k \in \mathcal{R}^N \quad (11)$$

$$y_k = \mathbf{H}_k \mathbf{x}_k + v_k, \quad y_k, v_k \in \mathcal{R} \quad (12)$$

$$z_k = \mathbf{H}_k \mathbf{x}_k, \quad z_k \in \mathcal{R}, \mathbf{H}_k \in \mathcal{R}^{1 \times N} \quad (13)$$

a state estimated value $\hat{\mathbf{x}}_{k|k}$ (or an output estimated value $\hat{z}_{k|k}$) satisfying

$$\sup_{x_0, \{\mathbf{w}_i\}, \{v_i\}} \frac{\sum_{i=0}^k \|e_{f,i}\|^2 / \rho}{\|\mathbf{x}_0 - \tilde{\mathbf{x}}_0\|_{\Sigma_0^{-1}}^2 + \sum_{i=0}^k \|\mathbf{w}_i\|^2 + \sum_{i=0}^k \|v_i\|^2 / \rho} < \gamma_f^2 \quad (14)$$

20

is given by a following hyper H_∞ filter of level γ_f .

[Mathematical Expression 14]

$$\tilde{z}_{k|k} = H_k \hat{x}_{k|k} \quad (15)$$

$$\hat{x}_{k|k} = \hat{x}_{k-1|k-1} + K_{s,k}(y_k - H_k \hat{x}_{k-1|k-1}) \quad (16)$$

$$K_{s,k} = \hat{\Sigma}_{k|k-1} H_k^T (H_k \hat{\Sigma}_{k|k-1} H_k^T + \rho)^{-1} \quad (17)$$

$$\begin{aligned} \hat{\Sigma}_{k|k} &= \hat{\Sigma}_{k|k-1} - \hat{\Sigma}_{k|k-1} C_k^T R_{e,k}^{-1} C_k \hat{\Sigma}_{k|k-1} \\ \hat{\Sigma}_{k+1|k} &= \hat{\Sigma}_{k|k} / \rho \end{aligned} \quad (18)$$

where,

$$\begin{aligned} e_{f,i} &= \tilde{z}_{i|i} - H_i x_i, \quad \hat{x}_{0|0} = \tilde{x}_0, \quad \hat{\Sigma}_{1|0} = \Sigma_0 \\ R_{e,k} &= R + C_k \hat{\Sigma}_{k|k-1} C_k^T \\ R &= \begin{bmatrix} \rho & 0 \\ 0 & -\rho \gamma_f^2 \end{bmatrix}, \quad C_k = \begin{bmatrix} H_k \\ H_k \end{bmatrix} \end{aligned} \quad (19)$$

$$0 < \rho = 1 - \chi(\gamma_f) \leq 1, \quad \gamma_f > 1 \quad (20)$$

$\chi(\gamma_f)$ is a monotonically decreasing function satisfying $\chi(1) = 1$ and $\chi(\infty) = 0$. Besides, a drive matrix G_k is generated as follows:

[Mathematical Expression 15]

$$G_k G_k^T = \chi(\gamma_f) \hat{\Sigma}_{k+1|k} = \frac{\chi(\gamma_f)}{\rho} \hat{\Sigma}_{k|k} \quad (21)$$

Where, a following existence condition must be satisfied.

10 [Mathematical Expression 16]

$$\hat{\Sigma}_{i|i}^{-1} = \hat{\Sigma}_{i|i-1}^{-1} + \frac{1 - \gamma_f^{-2}}{\rho} H_i^T H_i > 0, \quad i = 0, \dots, k \quad (22)$$

The feature of the hyper H_∞ filter is that the generation of robustness in the state estimation and the optimization of the forgetting factor ρ are simultaneously performed.

15 When the hyper H_∞ filter satisfies the existence condition, the inequation of expression (14) is always satisfied. Thus, in the case where the disturbance energy of the denominator of expression (14) is limited, the total sum of the square estimated error of the numerator becomes bounded, and the estimated error after a certain time has to become 0.

20 This means that when γ_f can be made small, the estimated value

$\hat{x}_{k|k}$ can more quickly follow the change of the state x_k .

Here, attention should be given to the fact that the algorithm of the hyper H_∞ filter of Theorem 1 is different from that of the normal H_∞ filter (non-patent document 4). Besides,
 5 when $\gamma_f \rightarrow \infty$, then $\rho = 1$ and $G_k = 0$, and the algorithm of the hyper H_∞ filter of Theorem 1 formally coincides with the algorithm of the Kalman filter.

The amount of calculation of the hyper H_∞ filter is $O(N^2)$, and this is not suitable for a real-time processing. However,
 10 when an observation matrix H_k has a shift characteristic $H_{k+1} = [u_{k+1}, H_k(1), H_k(2), \dots, H_k(N-1)]$, a fast algorithm of the amount of calculation $O(N)$ has been developed (non-patent document 2, non-patent document 3).

[0016]

15 Theorem 2 (fast H_∞ filter)

When the observation matrix H_k satisfies the shift characteristic, the hyper H_∞ filter having $\Sigma_0 = \varepsilon_0 I > 0$ can be executed by a following expression and with the amount of calculation $O(N)$.

20 [Mathematical Expression 17]

$$\hat{x}_{k|k} = \hat{x}_{k-1|k-1} + K_{s,k}(y_k - H_k \hat{x}_{k-1|k-1}) \quad (23)$$

$$K_{s,k} = \frac{K_k(:, 1)}{1 + \gamma_f^{-2} H_k K_k(:, 1)} \in \mathcal{R}^{N \times 1} \quad (24)$$

$$K_k = m_k - D_k \mu_k \in \mathcal{R}^{N \times 2} \quad (25)$$

$$D_k = [D_{k-1} - m_k W \eta_k][1 - \mu_k W \eta_k]^{-1} \quad (26)$$

$$\eta_k = c_{k-N} + C_k D_{k-1} \quad (26)$$

$$\begin{bmatrix} m_k \\ \mu_k \end{bmatrix} = \check{K}_k, \quad m_k \in \mathcal{R}^{N \times 2}, \mu_k \in \mathcal{R}^{1 \times 2} \quad (27)$$

$$\check{K}_k = \begin{bmatrix} S_k^{-1} e_k^T \\ K_{k-1} + A_k S_k^{-1} e_k^T \end{bmatrix} \quad (28)$$

$$\begin{aligned} S_k &= \rho S_{k-1} + e_k^T W e_k, \quad e_k = c_k + C_{k-1} A_k \\ A_k &= A_{k-1} - K_{k-1} W e_k, \quad \tilde{e}_k = c_k + C_{k-1} A_{k-1} \end{aligned} \quad (29)$$

Where, $C_k = \begin{bmatrix} H_k \\ H_k \end{bmatrix}$, $W = \begin{bmatrix} 1 & 0 \\ 0 & -\gamma_f^{-2} \end{bmatrix}$

$c_k \in R^{2 \times 1}$ is a first column vector of $C_k = [c_k, \dots, c_{k-N+1}]$, $c_{k-i} = 0_{2 \times 1}$ and $k-i < 0$ are assumed, and initial values are set to be $k_0 = 0_{N \times 2}$, $A_0 = 0_{N \times 1}$, $S_0 = 1/\epsilon_0$, $D_0 = 0_{N \times 1}$, and $\hat{X}_{0|0} = 0_{N \times 1}$. Where,
5 $0_{m \times n}$ denotes an $m \times n$ zero matrix.

At this time, a following scalar existence condition must be satisfied.

[Mathematical Expression 18]

$$-\varrho \hat{\Xi}_i + \rho \gamma_f^2 > 0, \quad i = 0, \dots, k \quad (30)$$

10 Where, $\varrho, \hat{\Xi}_i$ are respectively defined by following expressions.

$$\varrho = 1 - \gamma_f^2, \quad \hat{\Xi}_i = \frac{\rho H_i K_{s,i}}{1 - H_i K_{s,i}} = \frac{\rho H_i K_i(:,1)}{1 - (1 - \gamma_f^{-2}) H_i K_i(:,1)} \quad (31)$$

[0017]

4. Means of the identification method of the embodiment of
15 the invention

4.1 Preparation

It is assumed that an input signal is expressed by an $M(\leq N)$ -th order AR model (autoregressive model), and a method of optimally generating an $(N+1) \times 2$ auxiliary gain matrix $K_k^{U,N}$
20 $= Q_k^{U,-1} C_k^{U,T}$ from an $M \times 2$ gain matrix is derived.

Where, Q_k^U is expressed by

[Mathematical Expression 19]

$$\check{Q}_k = \rho \check{Q}_{k-1} + \check{C}_k^T W \check{C}_k \quad (32)$$

and $C_k^U = [C_k \ c_{k-N}] = [c_k \ c_{k-1}]$ is established (non-patent
25 document 2).

[0018]

[Lemma 1]

When an input signal is expressed by the $M(\leq N)$ -th order AR model, the auxiliary gain matrix $K_k^{U^N}$ is given by a following expression.

5 [Mathematical Expression 20]

$$\check{K}_k^N = \begin{bmatrix} \mathbf{0}_{(N-M+1) \times 2} \\ \check{K}_{k-N+M-1}^{M-1} \end{bmatrix} + \sum_{i=0}^{N-M} \frac{1}{S_{M,k-i}} \begin{bmatrix} \mathbf{0}_{i \times 2} \\ \mathbf{e}_{M,k-i}^T \\ \mathbf{A}_{k-i}^M \mathbf{e}_{M,k-i}^T \\ \mathbf{0}_{(N-M-i) \times 2} \end{bmatrix} \quad (33)$$

Where, $\mathbf{e}_{M,k} = \mathbf{c}_k + \mathbf{C}_{k-1}^M \mathbf{A}_k^M$, $\mathbf{C}_{k-1}^M = \mathbf{C}_{k-1}(:, 1:M)$, $K_{k-N+M-1}^{U^{M-1}} = K_{k-N+M-1}(1:M, :)$. Here, $\mathbf{C}_{k-1}(:, 1:M)$ denotes a matrix including the first column to the M -th column of $\mathbf{C}_{k-1}$.

10 (Proof) See "7. Proof of lemma" (described later).

[0019]

[Lemma 2]

When an input signal is expressed by the $M(\leq N)$ -th order AR model, the auxiliary gain matrix $K_k^{U^N}$ is equivalent to a
15 following expression.

[Mathematical Expression 21]

$$\check{K}_k^N = \begin{bmatrix} \mathbf{0}_{(N-M+1) \times 2} \\ \check{K}_{k-N+M-1}^{M-1} \end{bmatrix} + \mathbf{G}_k^N \quad (34)$$

Where,

$$\begin{aligned} & \begin{bmatrix} \mathbf{G}_k^N \\ \mathbf{0}_{1 \times 2} \end{bmatrix} \\ &= \begin{bmatrix} \mathbf{0}_{1 \times 2} \\ \mathbf{G}_{k-1}^N \end{bmatrix} + \frac{1}{S_{M,k}} \begin{bmatrix} \mathbf{e}_{M,k}^T \\ \mathbf{A}_k^M \mathbf{e}_{M,k}^T \\ \mathbf{0}_{(N-M+1) \times 2} \end{bmatrix} \\ & \quad - \frac{1}{S_{M,k-N+M-1}} \begin{bmatrix} \mathbf{0}_{(N-M+1) \times 2} \\ \mathbf{e}_{M,k-N+M-1}^T \\ \mathbf{A}_{k-N+M-1}^M \mathbf{e}_{M,k-N+M-1}^T \end{bmatrix} \end{aligned} \quad (35)$$

20 $\mathbf{G}_0^N = \mathbf{O}_{(N+1) \times 2}$, $K_{k-N+M-1}^{U^M} = \mathbf{O}_{(M+1) \times 2}$, $k-N+M-1 \leq 0$.

(Proof) See "7. Proof of lemma" (described later)

[0020]

[Lemma 3]

When an input signal is expressed by the $M(\leq N)$ -th order
 5 AR model, a gain matrix K_k is expressed by a following
 expression.

[Mathematical Expression 22]

$$K_k = m_k - D_k \mu_k \quad (36)$$

Where,

$$\begin{aligned} D_k &= \begin{bmatrix} 0_{N-M} \\ D_k^M \end{bmatrix}, \quad D_k^M = \frac{D_{k-1}^M - m_k(N-M+1:N,:)W\eta_{M,k}}{1 - \mu_k W\eta_{M,k}} \\ \eta_{M,k} &= c_{k-N} + \underline{C}_k^M D_{k-1}^M \\ \begin{bmatrix} m_k \\ \mu_k \end{bmatrix} &= \check{K}_k^N, \quad m_k \in \mathcal{R}^{N \times 2}, \mu_k \in \mathcal{R}^{1 \times 2} \\ \underline{C}_k^M &= C_k(:, N-M+1:N) \end{aligned} \quad (37)$$

10

Here, $m_k(M:N,:) = [m_k(M,:), \dots, m_k(N,:)]^T$, and $m_k(i,:)$ is the
 i -th row vector of m_k .

(Proof) See "7. Proof of lemma" (described later)

[0021]

15

FIG. 1 is an explanatory view showing update of a gain
 matrix of an order-recursive fast H_∞ filter.

This figure shows the summary of the above. By this,
 it is understood that

$$K_{k-N+M-1}(1:M,:) = K_{k-1}(N-M+1:N,:)$$

20

is theoretically established.

This point will be explained below.

$K_{k-N+M-1}^M$ including the first to the M -th row of the $N \times 2$
 gain matrix $K_{k-N+M-1}$ is extrapolated by using A_{k-i}^M and $S_{M,k-i}$, and
 after the $(N+1) \times 2$ auxiliary gain matrix $K_k^{U,N}$ is generated, the
 25 gain matrix K_k at a next time is obtained using D_k^M , and this

is repeated hereafter.

[0022]

4.2 Derivation of the order-recursive fast H_∞ filter

Next, a fast H_∞ filter having an optimum expanded filter
5 gain will be described.

[0023]

Theorem 3 (order-recursive fast H_∞ filter)

When an input signal is expressed by the $M(\leq N)$ -th order
AR model, the fast H_∞ filter is executed by a following
10 expression and with the amount of calculation $3N+O(M)$.

[Mathematical Expression 23]

$$\hat{\mathbf{x}}_{k|k} = \hat{\mathbf{x}}_{k-1|k-1} + \mathbf{K}_{s,k}(\mathbf{y}_k - \mathbf{H}_k \hat{\mathbf{x}}_{k-1|k-1}) \quad (38)$$

$$\mathbf{K}_{s,k} = \frac{\mathbf{K}_k(:, 1)}{1 + \gamma_f^{-2} \mathbf{H}_k \mathbf{K}_k(:, 1)} \in \mathcal{R}^{N \times 1}$$

$$\mathbf{K}_k = \mathbf{m}_k - \mathbf{D}_k \boldsymbol{\mu}_k, \quad \mathbf{D}_k = \begin{bmatrix} \mathbf{0}_{N-M} \\ \mathbf{D}_k^M \end{bmatrix} \quad (39)$$

$$\mathbf{D}_k^M = \frac{\mathbf{D}_{k-1}^M - \mathbf{m}_k(N-M+1:N, :) \mathbf{W} \boldsymbol{\eta}_{M,k}}{1 - \boldsymbol{\mu}_k \mathbf{W} \boldsymbol{\eta}_{M,k}}$$

$$\boldsymbol{\eta}_{M,k} = \mathbf{c}_{k-N} + \mathbf{C}_k^M \mathbf{D}_{k-1}^M \quad (40)$$

$$\begin{bmatrix} \mathbf{m}_k \\ \boldsymbol{\mu}_k \end{bmatrix} = \check{\mathbf{K}}_k^N, \quad \mathbf{m}_k \in \mathcal{R}^{N \times 2}, \quad \boldsymbol{\mu}_k \in \mathcal{R}^{1 \times 2} \quad (41)$$

$$\check{\mathbf{K}}_k^N = \begin{bmatrix} \mathbf{0}_{(N-M+1) \times 2} \\ \check{\mathbf{K}}_{k-N+M-1}^{M-1} \end{bmatrix} + \mathbf{G}_k^N, \quad \check{\mathbf{K}}_{k-N+M-1}^{M-1} = \mathbf{K}_{k-N+M-1}(1:M, :) \quad (42)$$

$$\begin{aligned} S_{M,k} &= \rho S_{M,k-1} + \mathbf{e}_{M,k}^T \mathbf{W} \tilde{\mathbf{e}}_{M,k}, \quad \mathbf{e}_{M,k} = \mathbf{c}_k + \mathbf{C}_{k-1}^M \mathbf{A}_k^M \\ \mathbf{A}_k^M &= \mathbf{A}_{k-1}^M - \mathbf{K}_{k-1}(1:M, :) \mathbf{W} \tilde{\mathbf{e}}_{M,k}, \quad \tilde{\mathbf{e}}_{M,k} = \mathbf{c}_k + \mathbf{C}_{k-1}^M \mathbf{A}_{k-1}^M \end{aligned} \quad (43)$$

Where, $\mathbf{G}_k^N$ is updated as follows:

$$\begin{aligned} \begin{bmatrix} \mathbf{G}_k^N \\ \mathbf{0}_{1 \times 2} \end{bmatrix} &= \begin{bmatrix} \mathbf{0}_{1 \times 2} \\ \mathbf{G}_{k-1}^N \end{bmatrix} + \begin{bmatrix} \mathbf{e}_{M,k}^T / S_{M,k} \\ \mathbf{A}_k^M \mathbf{e}_{M,k}^T / S_{M,k} \\ \mathbf{0}_{(N-M+1) \times 2} \end{bmatrix} \\ &\quad - \begin{bmatrix} \mathbf{0}_{(N-M+1) \times 2} \\ \mathbf{e}_{M,k-N+M-1}^T / S_{M,k-N+M-1} \\ \mathbf{A}_{k-N+M-1}^M \mathbf{e}_{M,k-N+M-1}^T / S_{M,k-N+M-1} \end{bmatrix} \end{aligned} \quad (44)$$

15 Where,

$$\underline{C}_k^M = C_k(:, N - M + 1 : N), \underline{C}_{k-1}^M = C_{k-1}(:, 1 : M), C_k = \begin{bmatrix} H_k \\ H_k \end{bmatrix}, W = \begin{bmatrix} 1 & 0 \\ 0 & -\gamma_f^{-2} \end{bmatrix}$$

$$e_{f,i} = z_{i|i}^v - H_i x_i, z_{i|i}^v = H_i \hat{x}_{i|i},$$

$c_k \in R^{2 \times 1}$ is the first column vector of $C_k = [c_k, \dots, c_{k-N+1}]$,

$c_{k-i} = 0_{2 \times 1}$, $k-i < 0$, and initial values are set to be $K_0 = 0_{N \times 2}$,

$$5 \quad G_0^N = 0_{(N+1) \times 2}, A_0^M = 0_{M \times 1}, S_{M,0} = 1/\varepsilon_0, D_0^M = 0_{M \times 1}, \hat{x}_{0|0} = x^v_0 = 0_{N \times 1}.$$

[0024]

Besides, a following scalar condition must be satisfied.

[Mathematical Expression 24]

$$-\varrho \hat{\Xi}_i + \rho \gamma_f^2 > 0, \quad i = 0, \dots, k \quad (45)$$

10 Here, $\varrho, \hat{\Xi}_i$ are respectively defined by following expressions.

$$\varrho = 1 - \gamma_f^2, \quad \hat{\Xi}_i = \frac{\rho H_i K_{s,i}}{1 - H_i K_{s,i}} = \frac{\rho H_i K_i(:, 1)}{1 - (1 - \gamma_f^{-2}) H_i K_i(:, 1)} \quad (46)$$

(Proof) It is obtained when the lemmas 1, 2 and 3 are applied to Theorem 2.

[0025]

15 4.3 Mounting of the order-recursive fast H_∞ filter

FIG. 2 shows a flowchart of the order-recursive fast H_∞ filter.

In order to reduce the amount of calculation, $K_k(:, 1) / (1 + \gamma_f^{-2} H_k K_k(:, 1))$ was directly used instead of $K_{s,k}$.

20 Hereinafter, the processing of the order-recursive fast H_∞ filter will be described with reference to a flowchart.

[Step S201, Initialization] The processing section 101 reads an initial state of a recursive equation from the storage section 105, or inputs the initial state from the input section

25 102, and determines it as shown in the figure.

[Step S203] The processing section 101 compares a time k with a maximum data number L . Incidentally, L denotes the

previously determined maximum data number. When the time k is larger than the maximum data number, the processing section 101 ends the processing, and when not larger than that, advance is made to a next step. (If unnecessary, the conditional sentence can be removed. Alternatively, restart may be made as the need arises.)

[Step S205, Input] The processing section 101 inputs an input u_k from the input section 102, and sets C_k^U as shown in the figure. Incidentally, the input u_k may be read from the storage section 105.

[Step S207, Forward prediction] The processing section 101 recursively determines variables $e_{M,k}$, A_k^M , $S_{M,k}$, $K_k(1:M,:)$ and the like by expression (43).

[Step S209, Extrapolation] The processing section 101 updates a matrix G_k^N by expression (44), and calculates an auxiliary gain matrix $K_k^{U,N}$ by expression (42).

[Step S211, Partition] The processing section 101 partitions the auxiliary gain matrix $K_k^{U,N}$ by expression (41).

[Step S213, Backward prediction] The processing section 101 calculates a variable D_k^M and a backward prediction error $\eta_{M,k}$ by expression (40).

[Step S215, Gain matrix] The processing section 101 calculates a gain matrix K_k by expression (39).

[Step S217, Filtering] The processing section 101 updates a filter equation of the fast H_∞ filter by expression (38). Here, in order to reduce the amount of calculation, $K_k(:,1)/(1+\gamma_f^{-2}H_kK_k(:,1))$ is directly used as a filter gain $K_{s,k}$.

[Step S219] The processing section 101 advances the time k ($k = k + 1$), returns to step S203, and continues as long as data exists or a specified number of times.

Incidentally, the processing section 101 may store a suitable intermediate value and a final value obtained at the respective steps of the calculation steps S205 to S217 of the H_∞ filter, a value of an existence condition and the like into
 5 the storage section 105 as the need arises, and may read them from the storage section 105.

Besides, it should be noted that the order-recursive fast H_∞ filter is completely coincident with the fast H_∞ filter when $M = N$ is established.

10 [0026]

FIG. 3 is a flowchart of check of a scalar existence condition.

In general, a check function of the existence condition of FIG. 3 is added to the flowchart of FIG. 2. This step can
 15 be executed by the processing section 101 at a suitable timing before or after a suitable one step or plural steps of the flowchart of FIG. 2 or FIG. 4 (described later) or the step (S219) of advancing the time k . $EXC(k)$ corresponds to the left side of the foregoing expression (45).

20 [0027]

4.4 Calculation of prediction variable

As a method of obtaining variables $e_{M,k-N+M-1}$, $A_{k-N+M-1}^M$, $S_{M,k-N+M-1}$ and $K_{k-N+M-1}^{U^{M-1}}$ ($= K_{k-N+M-1}^M = K_{k-N+M-1}(1:M,:)$) at the Extrapolation (step S209) of FIG. 2, there are following two
 25 methods.

1) Values of the variables obtained at the respective steps are held on a memory during $N-M$ steps.

2) Values of the variables at a time $t_{k-N+M-1}$ are also again calculated at the respective steps (see FIG. 4 described
 30 later).

[0028]

In general, the method of 1) is suitable for a DSP (Digital Signal Processor) having a large storage capacity, and the method of 2) is often suitable for a normal DSP, and either
 5 of the methods may be used.

[0029]

FIG. 4 is a flowchart of a calculation method of values of prediction variables at the time $t_{k-N+M-1}$.

Hereinafter, a calculation processing of the values of
 10 the prediction variables at the time $t_{k-N+M-1}$ will be described with reference to the flowchart. The processing section 101 calculates the respective variables based on the flowchart, and uses the respective variables when step S209 or the like of the flowchart of FIG. 2 is calculated.

15 [Step S401, Initialization] The processing section 101 reads an initial state of a recursive equation from the storage section 105, or inputs the initial state from the input section 102, and determines it as shown in the figure.

[Step S403] The processing section 101 compares a time k with
 20 a maximum data number L . Incidentally, L denotes the previously determined maximum data number. When the time k is larger than the maximum data number, the processing section 101 ends the processing, and when not larger than that, advance is made to a next step. (If unnecessary, the conditional sentence can be removed. Alternatively, restart may be made
 25 as the need arises.)

[Step S405, Input] An input u_k is inputted from the input section 102, and C_k^u is set as shown in the figure. Incidentally, the input u_k may be read from the storage section 105.

30 [Step S407, Forward prediction] The processing section 101

recursively determines variables $e_{M,k}$, A_k^M , $S_{M,k}$, K_{k-1}^M and the like as shown in the figure (see expression (43)).

[Step S409, Extrapolation] The processing section 101 calculates an auxiliary gain matrix K_k^{UM} as shown in the figure
5 (see expression (42)).

[Step S411, Partition] The processing section 101 partitions the auxiliary gain matrix K_k^{UM} as shown in the figure (see expression (41)).

[Step S413, Backward prediction] The processing section 101
10 calculates a variable D_k^M and a backward prediction error $\eta_{M,k}$ as shown in the figure (see expression (40)).

[Step S415, Gain matrix] The processing section 101 calculates a gain matrix K_k^M as shown in the figure (see expression (39)).

15 [Step S417] The processing section 101 advances the time k ($k = k + 1$), returns to step S403, and continues as long as data exists or a specified number of times.

Incidentally, the processing section 101 may store a suitable intermediate value and a final value obtained at the
20 respective steps of the calculation steps S405 to S415 of the H_∞ filter, a value of an existence condition and the like into the storage section 105 as the need arises, or may read them from the storage section 105.

[0030]

25 4.5 Backward prediction error

For numerical stabilization, instead of the backward prediction error η_k ,

[Mathematical Expression 25]

$$\tilde{\eta}_k = \eta_k + \beta(\eta_k - \rho^{-N} S_k \mu_k^T) \quad (47)$$

can be adopted.

FIG. 5 is a flowchart of a numerically stabilized fast H_∞ filter (order-recursive fast H_∞ filter at $M = N$).

In general, a check function of an existence condition
 5 of FIG. 3 is added to this flowchart. Besides, β denotes a control parameter, and β is generally made $\beta = 1.0$. This stabilizing method can be applied also to a case of $M < N$.

Hereinafter, the processing of the numerically
 10 stabilized fast H_∞ filter will be described with reference to the flowchart.

[Step S501, Initialization] The processing section 101 reads an initial state of a recursive equation from the storage section 105, or inputs the initial state from the input section 102, and determines it as shown in the figure.

15 [Step S503] The processing section 101 compares a time k with a maximum data number L . Incidentally, L denotes the previously determined maximum data number. When the time k is larger than the maximum data number, the processing section 101 ends the processing, and when not larger than that, advance
 20 is made to a next step. (If unnecessary, the conditional sentence can be removed. Alternatively, restart may be made as the need arises.)

[Step S505, Input] An input u_k is inputted from the input section 102, and C_k^U is set as shown in the figure. Incidentally,
 25 the input u_k may be read from the storage section 105.

[Step S507, Forward prediction] The processing section 101 recursively determines variables $e_{M,k}$, A_k , S_k , K_{k-1} and the like as shown in the figure (see expression (43)).

[Step S509, Extrapolation] The processing section 101
 30 calculates an auxiliary gain matrix $K_k^{U,N}$ as shown in the figure

(see expression (42)).

[Step S511, Partition] The processing section 101 partitions the auxiliary gain matrix K_k^{UN} as shown in the figure (see expression (41)).

5 [Step S513, Stabilized backward prediction] The processing section 101 calculates a variable D_k^M and a backward prediction error $\tilde{\eta}_k$ as shown in the figure (see expression (40)). Here, for numerical stabilization, $\tilde{\eta}_k$ (expression (47)) is adopted instead of the backward prediction error η_k .

10 [Step S515, Gain matrix] The processing section 101 calculates a gain matrix K_k^M as shown in the figure (see expression (39)).

[Step S517, Filtering] The processing section 101 updates a filter equation of the fast H_∞ filter by expression (38). Here, in order to reduce the amount of calculation, $K_k(:,1)/(1+\gamma_f^{-2}H_kK_k(:,1))$ is directly used as the filter gain $K_{s,k}$.

[Step S519] The processing section 101 advances the time k ($k = k + 1$), returns to step S503, and continues as long as data exists or a specified number of times.

20 Incidentally, the processing section 101 may store a suitable intermediate value and a final value obtained at the respective steps of the calculation steps S505 to S517 of the H_∞ filter, a value of an existence condition and the like into the storage section 105 as the need arises, or may read them
25 from the storage section 105.

[0031]

5. Comparison result

FIG. 12 is a view of result of comparison between the
30 amount of calculation of the fast H_∞ filter (FHF) and that of

the order-recursive fast H_∞ filter (OR-FHF).

However, this result is obtained in the case where calculation is performed in accordance with the expressions, and the amount of calculation can be further reduced by
5 contrivance. Besides, division of a vector by a scalar can be counted as multiplication by taking the reciprocal of the scalar.

By this, when $M \ll N$ is established, the number of times of multiplication required for the order-recursive fast H_∞
10 filter becomes about $3N$, and it is understood that the amount of calculation can be greatly reduced as compared with the fast H_∞ filter.

[0032]

15 6. Echo canceller

6.1 Preparation

Hereinafter, an example of an echo canceller is adopted as the embodiment, and the operation of the identification
algorithm is confirmed. Before that, the echo canceller will
20 be described in brief.

FIG. 6 is an explanatory view of a communication system and an echo.

In a long distance telephone circuit such as an international telephone, a four-wire circuit is used from the
25 reason of signal amplification and the like. On the other hand, since a subscriber's circuit has a relatively short distance, a two-wire circuit is used. A hybrid transformer as shown in the figure is introduced at a connection part between the two-wire circuit and the four-wire circuit, and impedance
30 matching is performed. When the impedance matching is

complete, a signal (sound) from a speaker B reaches only a speaker A. However, in general, it is difficult to realize the complete matching, and there occurs a phenomenon in which part of the received signal leaks to the four-wire circuit, and returns to the receiver (speaker A) after being amplified. This is an echo. As a transmission distance becomes long (as a delay time becomes long), the influence of the echo becomes large, and the quality of a telephone call is remarkably deteriorated (in the pulse transmission, even in the case of short distance, the deterioration of a telephone call due to the echo can be a problem).

[0033]

FIG. 7 is a principle view of an echo canceller.

As shown in the figure, the echo canceller is introduced, an impulse response of an echo path is successively estimated by using a received signal which can be directly observed and an echo, and a pseudo-echo obtained by using it is subtracted from the actual echo to cancel the echo and to remove it.

[0034]

The estimation of the impulse response of the echo path is performed so that the mean square error of a residual echo e_k becomes minimum. At this time, elements to interfere with the estimation of the echo path are circuit noise and a signal (sound) from the speaker A. In general, when two speakers simultaneously start to speak (double talk), the estimation of the impulse response is suspended. Besides, since the impulse response length of the hybrid transformer is, for example, about 50 [ms], when the sampling period is made 125 [μ s], the order of the impulse response of the echo path becomes actually about 400.

Next, a mathematical model of this echo canceling problem is created. First, when consideration is given to the fact that the received signal $\{u_k\}$ becomes the input signal to the echo path, by the impulse response $\{h_i[k]\}$ of the echo path, an observed value $\{y_k\}$ of an echo $\{d_k\}$ is expressed by a following expression.

[Mathematical Expression 26]

$$y_k = d_k + v_k = \sum_{i=0}^{N-1} h_i[k] u_{k-i} + v_k, \quad k = 0, 1, 2, \dots \quad (48)$$

Here, u_k and y_k respectively denote the received signal and the observed value of the echo at a time t_k ($= kT$; T is a sampling period), v_k denotes circuit noise of a mean value 0 at the time t_k , and it is assumed that a tap number N is known. At this time, when an estimated value $\{\hat{h}_i[k]\}$ of the impulse response is obtained every moment, the pseudo-echo can be generated by using that as described below.

[Mathematical Expression 27]

$$\hat{d}_k = \sum_{i=0}^{N-1} \hat{h}_i[k] u_{k-i}, \quad k = 0, 1, 2, \dots \quad (49)$$

When this is subtracted from the echo ($y_k - \hat{d}_k \approx 0$), and the echo can be cancelled. Where, it is assumed that if $k-i < 0$, then $u_{k-i} = 0$.

From the above, the canceling problem can be reduced to the problem of successively estimating the impulse response $\{h_i[k]\}$ of the echo path from the received signal $\{u_k\}$ which can be directly observed and the observed value $\{y_k\}$ of the echo.

In general, in order to apply the H_∞ filter to the echo canceller, first, expression (48) must be expressed by a state space model including a state equation and an observation

equation. Then, when $\{h_i[k]\}$ is made a state variable $\mathbf{x}_k$, and a variance of about w_k is allowed, the following state space model can be established for the echo path.

[Mathematical Expression 28]

$$\mathbf{x}_{k+1} = \mathbf{x}_k + \mathbf{G}_k \mathbf{w}_k, \quad \mathbf{x}_k, \mathbf{w}_k \in \mathcal{R}^N \quad (50)$$

$$y_k = \mathbf{H}_k \mathbf{x}_k + v_k, \quad y_k, v_k \in \mathcal{R} \quad (51)$$

$$z_k = \mathbf{H}_k \mathbf{x}_k, \quad z_k \in \mathcal{R}, \mathbf{H}_k \in \mathcal{R}^{1 \times N} \quad (52)$$

5

Where,

$$\mathbf{x}_k = [h_0[k], \dots, h_{N-1}[k]]^T, \quad \mathbf{w}_k = [w_k(1), \dots, w_k(N)]^T$$

$$\mathbf{H}_k = [u_k, \dots, u_{k-N+1}]$$

[0035]

10 6.2 Confirmation of operation

FIG. 13 is a view showing an impulse response of an echo path.

With respect to the case where the impulse response of the echo path is temporally invariable ($h_i[k]=h_i$), and for example, the tap number N is 48, the operation of the fast algorithm is confirmed by using a simulation. At this time, the observed value y_k of the echo is expressed by a following expression.

[Mathematical Expression 29]

$$y_k = \sum_{i=0}^{63} h_i u_{k-i} + v_k \quad (53)$$

20

Where, the values of FIG. 13 are used for the impulse response $\{h_i\}_{i=0}^{23}$, and the other $\{h_i\}_{i=24}^{63}$ is made 0. Besides, it is assumed that v_k is stationary Gaussian white noise having a mean value of 0 and a variance $\sigma_v = 1.0 \times 10^{-4}$, and the sampling period T is made 1.0 for convenience.

25

Besides, the received signal $\{u_k\}$ is approximated by a secondary AR model as follows:

[Mathematical Expression 30]

$$u_k = \alpha_1 u_{k-1} + \alpha_2 u_{k-2} + w'_k \quad (54)$$

Where, $\alpha_1 = 0.7$, $\alpha_2 = 0.1$, and w'_k is the stationary Gaussian white noise having a mean value of 0 and a variance $\sigma_{w'}^2 = 0.04$.

5 [0036]

FIG. 8 is a view showing an estimation result (performance evaluation) of the impulse response by the order-recursive fast H_∞ filter at $M = 2$.

Here, FIG. 8A shows an estimated value ($\hat{X}_{256|256}$) of the
10 impulse response at $k = 256$ (broken line indicates a true value), and FIG. 8B shows a convergence characteristic thereof. Where, the vertical axis of FIG. 8B indicates $\|x_k - \hat{x}_{k|k}\|^2 = \sum_{i=0}^{63} (h_i - \hat{x}_k(i+1))^2$. By this, it is understood that the impulse response of the system can be excellently estimated by the
15 order-recursive fast H_∞ filter. Where, $\rho = 1 - \chi(\gamma_f)$, $\chi(\gamma_f) = \gamma_f^{-2}$, $\hat{x}_{0|0} = 0$, $\gamma_f = 10.0$, $\hat{\Sigma}_{1|0} = \varepsilon_0 I$, and $\varepsilon_0 = 10.0$ are assumed, and the calculation is performed at MATLAB (double precision).

FIG. 9 is a convergence characteristic view of the order-recursive fast H_∞ filter with respect to sound input (in
20 this example, $N = 512$, $M = 20$, $\gamma_f = 54.0$).

Here, it is assumed that the order of the impulse response of an unknown system is 512, and the sound is a 20th order AR model. Besides, $\gamma_f = 54.0$ and $\varepsilon_0 = 1.0$ are assumed, and the calculation is performed at MATLAB (double precision). By
25 this, it is understood that even when the input is sound, the order-recursive fast H_∞ filter has excellent performance.

FIG. 10 is a view of comparison of an existence condition. This figure shows temporal changes of values of the left side (EXC(k)) of the scalar existence condition with respect to the
30 fast H_∞ filter (order-recursive fast H_∞ filter at $M = N$) (Fig.

10A) and a numerically stabilized fast H_∞ filter (FIG. 10B) (in this example, $N = 256$, $\gamma_f = 42.0$).

By this, in the case of the fast H_∞ filter, the value of $EXC(k)$ becomes negative at about 45000 steps, and the filter is stopped. On the other hand, in the numerically stabilized fast H_∞ filter, $EXC(k)$ always keeps a positive value in this section, and the existence condition is satisfied. However, the calculation is performed at single precision, and the same sound signal is used for each input.

10

[0037]

7. Proof of lemma

7.1 Proof of lemma 1

When the dimension of a state vector is M , a following expression is obtained from expression (28).

15

[Mathematical Expression 31]

$$\check{K}_k^M = \begin{bmatrix} \mathbf{0}_{1 \times 2} \\ \check{K}_{k-1}^{M-1} \end{bmatrix} + \frac{1}{S_{M,k}} \begin{bmatrix} \mathbf{e}_{M,k}^T \\ \mathbf{A}_k^M \mathbf{e}_{M,k}^T \end{bmatrix} \quad (55)$$

When this is applied to the case of the dimension of $M+1$, an auxiliary gain matrix $K_k^{U^{M+1}}$ is obtained.

20

[Mathematical Expression 32]

$$\check{K}_k^{M+1} = \begin{bmatrix} \mathbf{0}_{1 \times 2} \\ \check{K}_{k-1}^M \end{bmatrix} + \frac{1}{S_{M+1,k}} \begin{bmatrix} \mathbf{e}_{M+1,k}^T \\ \mathbf{A}_k^{M+1} \mathbf{e}_{M+1,k}^T \end{bmatrix} \quad (56)$$

On the other hand, when an input signal can be expressed by an M -th order AR model, $e_{M,k} = \min\{e_{m,k}\}$ and $\tilde{e}_{M,k} = \min\{\tilde{e}_{m,k}\}$ are established for $m \geq M$. By this,

25

[Mathematical Expression 33]

$$\begin{aligned}
e_{m,k} &= c_k + C_{k-1}^m A_k^m = c_k + C_{k-1}^M A_k^M = e_{M,k} \\
\tilde{e}_{m,k} &= c_k + C_{k-1}^M A_{k-1}^M = \tilde{e}_{M,k} \\
A_k^m e_{m,k}^T &= \begin{bmatrix} A_k^M e_{M,k}^T \\ 0_{(m-M) \times 1} \end{bmatrix} \\
S_{m,k} &= S_{M,k} = \rho S_{M,k-1} + e_{M,k}^T W \tilde{e}_{M,k}
\end{aligned} \tag{57}$$

At this time,

$$\check{Q}_k^{M+1} \begin{bmatrix} 0 \\ 1 \\ A_{k-1}^M \end{bmatrix} = \begin{bmatrix} 0 \\ S_{M,k-1} \\ 0_M \end{bmatrix}$$

is established. Thus, a following expression is obtained.

5 [Mathematical Expression 34]

$$\begin{aligned}
\check{K}_k^{M+1} &= \begin{bmatrix} 0_{1 \times 2} \\ \check{K}_{k-1}^M \end{bmatrix} + \frac{1}{S_{M,k}} \begin{bmatrix} e_{M,k}^T \\ A_k^M e_{M,k}^T \\ 0_{1 \times 2} \end{bmatrix} \\
&= \begin{bmatrix} 0_{1 \times 2} \\ 0_{1 \times 2} \\ \check{K}_{k-2}^{M-1} \end{bmatrix} + \frac{1}{S_{M,k-1}} \begin{bmatrix} 0_{1 \times 2} \\ e_{M,k-1}^T \\ A_{k-1}^M e_{M,k-1}^T \end{bmatrix} + \frac{1}{S_{M,k}} \begin{bmatrix} e_{M,k}^T \\ A_k^M e_{M,k}^T \\ 0_{1 \times 2} \end{bmatrix}
\end{aligned}$$

Similarly, when the repetition is made up to N, at last, by using A_{k-1}^M , $S_{M,k-1}$ satisfying

[Mathematical Expression 35]

$$\check{Q}_k^N \begin{bmatrix} 0_i \\ 1 \\ A_{k-i}^M \\ 0_{N-M-i} \end{bmatrix} = \begin{bmatrix} 0_i \\ S_{M,k-i} \\ 0_M \\ 0_{N-M-i} \end{bmatrix}$$

10

that is,

$$\check{Q}_{k-i}^M \begin{bmatrix} 1 \\ A_{k-i}^M \end{bmatrix} = \begin{bmatrix} S_{M,k-i} \\ 0_M \end{bmatrix}$$

the auxiliary gain matrix $K_k^{U,N}$ can be expressed as follows:

[Mathematical Expression 36]

$$\check{\mathbf{K}}_k^N = \begin{bmatrix} \mathbf{0}_{(N-M+1) \times 2} \\ \check{\mathbf{K}}_{k-N+M-1}^{M-1} \end{bmatrix} + \sum_{i=0}^{N-M} \frac{1}{S_{M,k-i}} \begin{bmatrix} \mathbf{0}_{i \times 2} \\ \mathbf{e}_{M,k-i}^T \\ \mathbf{A}_{k-i}^M \mathbf{e}_{M,k-i}^T \\ \mathbf{0}_{(N-M-i) \times 2} \end{bmatrix}$$

[0038]

7.2 Proof of lemma 2

An auxiliary variable G_k^N is defined as

5 [Mathematical Expression 37]

$$\mathbf{G}_k^N = \sum_{i=0}^{N-M} \frac{1}{S_{M,k-i}} \begin{bmatrix} \mathbf{0}_{i \times 2} \\ \mathbf{e}_{M,k-i}^T \\ \mathbf{A}_{k-i}^M \mathbf{e}_{M,k-i}^T \\ \mathbf{0}_{(N-M-i) \times 2} \end{bmatrix}$$

At this time, when attention is paid to $G_k^N(i-1, :) = G_{k-1}^N(i, :)$, it becomes

[Mathematical Expression 38]

$$\begin{aligned} & \begin{bmatrix} \mathbf{G}_k^N \\ \mathbf{0}_{1 \times 2} \end{bmatrix} - \begin{bmatrix} \mathbf{0}_{1 \times 2} \\ \mathbf{G}_{k-1}^N \end{bmatrix} \\ &= \frac{1}{S_{M,k}} \begin{bmatrix} \mathbf{e}_{M,k}^T \\ \mathbf{A}_k^M \mathbf{e}_{M,k}^T \\ \mathbf{0}_{(N-M+1) \times 2} \end{bmatrix} - \frac{1}{S_{M,k-N+M-1}} \begin{bmatrix} \mathbf{0}_{(N-M+1) \times 2} \\ \mathbf{e}_{M,k-N+M-1}^T \\ \mathbf{A}_{k-N+M-1}^M \mathbf{e}_{M,k-N+M-1}^T \end{bmatrix} \end{aligned}$$

10

By this, expression (35) is established. Thus, the auxiliary gain matrix $\mathbf{K}_k^{U,N}$ is equivalent to expression (34) (expression (42)).

[0039]

15 7.3 Proof of lemma 3

When an input signal is expressed by an $M(\leq N)$ -th order AR model, it becomes

[Mathematical Expression 39]

$$\begin{aligned}
\eta_k &= c_{k-N} + C_k D_{k-1} = c_{k-N} + \underline{C}_k^M D_{k-1}^M \\
\check{Q}_{k-N+M}^M \begin{bmatrix} D_k^M \\ 1 \end{bmatrix} &= \begin{bmatrix} 0_M \\ (F_k^M)^{-1} \end{bmatrix} \\
\left(\check{Q}_k^N \begin{bmatrix} D_k \\ 1 \end{bmatrix} = \check{Q}_k^N \begin{bmatrix} 0_{N-M} \\ D_k^M \\ 1 \end{bmatrix} \right)
\end{aligned} \tag{58}$$

When attention is paid to this, expression (36) and expression (37) are obtained by a similar method to non-patent document 2.

5

Industrial Applicability

[0040]

The fast identification method of the invention can be applied to the identification of a large-scale sound system or communication system, and is effective for an echo canceller in a loudspeaker or a television meeting system, active noise control, sound field reproduction and the like. Besides, by the development of the numerically stabilizing method, the operation can be made more stably even at single precision, and higher performance can be realized at low cost.

In a normal civil communication equipment or the like, in general, calculation is often performed at single precision from the viewpoint of cost and speed. Thus, the invention, as the practical fast identification method, would have the effect in various industrial fields.

Claims

1. A system identification device for performing fast
real-time identification of a time invariable or time variable
5 system, comprising:

a filter that is robust against a disturbance by
determining that a maximum energy gain to a filter error from
the disturbance, as an evaluation criterion, is restricted to
be smaller than a previously given upper limit γ_f^2 ,

10 wherein

the filter satisfies an H_∞ evaluation criterion as
indicated by following expression (14) with respect to a state
space model as indicated by following expressions (11) to (13),

when an input signal is expressed by an $M(\leq N)$ -th order
15 autoregressive model (AR model), the filter is given by
following expressions (38) to (44), and

the filter satisfies a scalar existence condition of
following expressions (45) and (46):

[Mathematical Expression 1]

$$\mathbf{x}_{k+1} = \mathbf{x}_k + \mathbf{G}_k \mathbf{w}_k, \quad \mathbf{w}_k, \mathbf{x}_k \in \mathcal{R}^N \quad (11)$$

$$y_k = \mathbf{H}_k \mathbf{x}_k + v_k, \quad y_k, v_k \in \mathcal{R} \quad (12)$$

$$z_k = \mathbf{H}_k \mathbf{x}_k, \quad z_k \in \mathcal{R}, \mathbf{H}_k \in \mathcal{R}^{1 \times N} \quad (13)$$

20

$$\sup_{x_0, \{w_i\}, \{v_i\}} \frac{\sum_{i=0}^k \|e_{f,i}\|^2 / \rho}{\|\mathbf{x}_0 - \tilde{\mathbf{x}}_0\|_{\Sigma_0^{-1}}^2 + \sum_{i=0}^k \|\mathbf{w}_i\|^2 + \sum_{i=0}^k \|v_i\|^2 / \rho} < \gamma_f^2 \quad (14)$$

[Mathematical Expression 2]

$$\hat{\mathbf{x}}_{k|k} = \hat{\mathbf{x}}_{k-1|k-1} + \mathbf{K}_{s,k}(\mathbf{y}_k - \mathbf{H}_k \hat{\mathbf{x}}_{k-1|k-1}) \quad (38)$$

$$\mathbf{K}_{s,k} = \frac{\mathbf{K}_k(:, 1)}{1 + \gamma_f^{-2} \mathbf{H}_k \mathbf{K}_k(:, 1)} \in \mathcal{R}^{N \times 1}$$

$$\mathbf{K}_k = \mathbf{m}_k - \mathbf{D}_k \boldsymbol{\mu}_k, \quad \mathbf{D}_k = \begin{bmatrix} \mathbf{0}_{N-M} \\ \mathbf{D}_k^M \end{bmatrix} \quad (39)$$

$$\mathbf{D}_k^M = \frac{\mathbf{D}_{k-1}^M - \mathbf{m}_k(N-M+1:N, :) \mathbf{W} \boldsymbol{\eta}_{M,k}}{1 - \boldsymbol{\mu}_k^T \mathbf{W} \boldsymbol{\eta}_{M,k}}$$

$$\boldsymbol{\eta}_{M,k} = \mathbf{c}_{k-N} + \mathbf{C}_k^M \mathbf{D}_{k-1}^M \quad (40)$$

$$\begin{bmatrix} \mathbf{m}_k \\ \boldsymbol{\mu}_k \end{bmatrix} = \check{\mathbf{K}}_k^N, \quad \mathbf{m}_k \in \mathcal{R}^{N \times 2}, \quad \boldsymbol{\mu}_k \in \mathcal{R}^{1 \times 2} \quad (41)$$

$$\check{\mathbf{K}}_k^N = \begin{bmatrix} \mathbf{0}_{(N-M+1) \times 2} \\ \check{\mathbf{K}}_{k-N+M-1}^{M-1} \end{bmatrix} + \mathbf{G}_k^N, \quad \check{\mathbf{K}}_{k-N+M-1}^{M-1} = \mathbf{K}_{k-N+M-1}(1:M, :) \quad (42)$$

$$\begin{aligned} S_{M,k} &= \rho S_{M,k-1} + \mathbf{e}_{M,k}^T \mathbf{W} \tilde{\mathbf{e}}_{M,k}, \quad \mathbf{e}_{M,k} = \mathbf{c}_k + \mathbf{C}_{k-1}^M \mathbf{A}_k^M \\ \mathbf{A}_k^M &= \mathbf{A}_{k-1}^M - \mathbf{K}_{k-1}(1:M, :) \mathbf{W} \tilde{\mathbf{e}}_{M,k}, \quad \tilde{\mathbf{e}}_{M,k} = \mathbf{c}_k + \mathbf{C}_{k-1}^M \mathbf{A}_{k-1}^M \end{aligned} \quad (43)$$

here, $\mathbf{G}_k^N$ is updated as follows:

$$\begin{aligned} \begin{bmatrix} \mathbf{G}_k^N \\ \mathbf{0}_{1 \times 2} \end{bmatrix} &= \begin{bmatrix} \mathbf{0}_{1 \times 2} \\ \mathbf{G}_{k-1}^N \end{bmatrix} + \begin{bmatrix} \mathbf{e}_{M,k}^T / S_{M,k} \\ \mathbf{A}_k^M \mathbf{e}_{M,k}^T / S_{M,k} \\ \mathbf{0}_{(N-M+1) \times 2} \end{bmatrix} \\ &\quad - \begin{bmatrix} \mathbf{0}_{(N-M+1) \times 2} \\ \mathbf{e}_{M,k-N+M-1}^T / S_{M,k-N+M-1} \\ \mathbf{A}_{k-N+M-1}^M \mathbf{e}_{M,k-N+M-1}^T / S_{M,k-N+M-1} \end{bmatrix} \end{aligned} \quad (44)$$

where,

$$\mathbf{C}_k(:, N-M+1:N), \mathbf{C}_{k-1}^M = \mathbf{C}_{k-1}(:, 1:M), \quad \mathbf{C}_k = \begin{bmatrix} \mathbf{H}_k \\ \mathbf{H}_k \end{bmatrix}, \quad \mathbf{W} = \begin{bmatrix} 1 & 0 \\ 0 & -\gamma_f^{-2} \end{bmatrix}$$

5

$$\mathbf{e}_{f,i} = \mathbf{z}_{i|i}^v - \mathbf{H}_i \mathbf{x}_i, \quad \mathbf{z}_{i|i}^v = \mathbf{H}_i \hat{\mathbf{x}}_{i|i}$$

($\mathbf{c}_k \in \mathcal{R}^{2 \times 1}$ is a first column vector of $\mathbf{C}_k = [\mathbf{c}_k, \dots, \mathbf{c}_{k-N+1}]$, $\mathbf{c}_{k-1} = \mathbf{0}_{2 \times 1}$ and $k-i < 0$ are assumed, and initial values are set to be $\mathbf{K}_0 = \mathbf{0}_{N \times 2}$, $\mathbf{G}_0^N = \mathbf{0}_{(N+1) \times 2}$, $\mathbf{A}_0^M = \mathbf{0}_{M \times 1}$, $S_{M,0} = 1/\epsilon_0$, $\mathbf{D}_0^M = \mathbf{0}_{M \times 1}$,

10 $\hat{\mathbf{x}}_{0|0} = \mathbf{x}^v_0 = \mathbf{0}_{N \times 1}$, here, $\mathbf{0}_{m \times n}$ denotes an $m \times n$ zero matrix)

[Mathematical Expression 3]

$$-\varrho \hat{\Xi}_i + \rho \gamma_f^2 > 0, \quad i = 0, \dots, k \quad (45)$$

here, $\varrho, \hat{\Xi}_i$ are respectively defined by following expressions:

$$\varrho = 1 - \gamma_f^2, \quad \hat{\Xi}_i = \frac{\rho \mathbf{H}_i \mathbf{K}_{s,i}}{1 - \mathbf{H}_i \mathbf{K}_{s,i}} = \frac{\rho \mathbf{H}_i \mathbf{K}_i(:,1)}{1 - (1 - \gamma_f^2) \mathbf{H}_i \mathbf{K}_i(:,1)} \quad (46)$$

where

$\mathbf{x}_k$: a state vector or simply a state; unknown, this is an object of estimation,

5 $\mathbf{x}_0$: an initial state; unknown,

$\mathbf{w}_k$: a system noise; unknown,

$\mathbf{v}_k$: an observation noise; unknown,

$\mathbf{y}_k$: an observation signal; input of the filter and known,

$\mathbf{z}_k$: an output signal, unknown,

10 $\mathbf{G}_k$: a drive matrix; becomes known at execution,

$\mathbf{H}_k$: an observation matrix; known,

$\hat{\mathbf{x}}_{k|k}$: an estimated value of the state $\mathbf{x}_k$ at a time k using observation signals $\mathbf{y}_0 - \mathbf{y}_k$; given by a filter equation,

$\mathbf{K}_{s,k}$: a filter gain; obtained from a gain matrix $\mathbf{K}_k$,

15 ρ : a forgetting factor; in a case of Theorem 1 - Theorem 3, when γ_f is determined, it is automatically determined by $\rho = 1 - \chi(\gamma_f)$,

Σ_0^{-1} : an inverse matrix of a weighting matrix expressing uncertainty of a state; Σ_0 is known,

20 N : a dimension (tap number) of a state vector; previously given,

M : an order of an AR model; previously given,

μ_k : $N+1$ th row vector of $\mathbf{K}_k^{U,N}$; obtained from $\mathbf{K}_k^{U,N}$,

$\mathbf{m}_k$: $N \times 2$ matrix including a first to an N -th row of $\mathbf{K}_k^{U,N}$; obtained from $\mathbf{K}_k^{U,N}$,

25 γ_f : attenuation level; given at design time

$\mathbf{D}_k^M$: a backward prediction coefficient vector; obtained from $\mathbf{m}_k$, $\eta_{M,k}$ and μ_k ,

$\mathbf{W}$: a weighting matrix; determined from γ_f ,

$\mathbf{A}_k^M$: a forward prediction coefficient vector; obtained from $\mathbf{K}_{k-1}$

and $e_{M,k}^{\sim}$,

C_k^M : a $2 \times M$ matrix including a 1st to an M -th column vector of C_k ; determined from the observation matrix H_k , and

$\underline{C}_k^M$: a $2 \times M$ matrix including an $N-M+1$ -th to an N -th column vector
5 of C_k ; determined from the observation matrix H_k .

2. The system identification device according to claim 1, wherein it is assumed that the input signal is expressed by the $M(\leq N)$ -th order autoregressive model (AR model), a
10 processing section of the filter optimally generates a $(N+1) \times 2$ auxiliary gain matrix $K_k^{U,N} = Q_k^{U,-1} C_k^{U,T}$ from an $M \times 2$ gain matrix, here, Q_k^U is expressed by
[Mathematical Expression 4]

$$\check{Q}_k = \rho \check{Q}_{k-1} + \check{C}_k^T W \check{C}_k \quad (32)$$

15 $C_k^U = [C_k \ C_{k-N}] = [C_k \ C_{k-1}]$,
[Mathematical Expression 5]
where,

$$C_k = \begin{bmatrix} H_k \\ H_k \end{bmatrix}, \quad W = \begin{bmatrix} 1 & 0 \\ 0 & -\gamma_f^{-2} \end{bmatrix}$$

20 3. The system identification device according to claim 1, wherein a processing section of the filter adopts a following expression $\tilde{\eta}_k$ instead of a backward prediction error η_k for numeral stabilization:
[Mathematical Expression 6]

25
$$\tilde{\eta}_k = \eta_k + \beta(\eta_k - \rho^{-N} S_k \mu_k^T) \quad (47)$$

4. The system identification device according to claim

1, wherein

a processing section of the filter includes a step of reading an initial state of a recursive equation from a storage section or inputting the initial state from an input section
5 and determining it,

the processing section includes a step of inputting an input u_k from the input section or reading it from the storage section and setting C_k^U , $K_k^U(1:M,:)$,

the processing section includes a step of recursively
10 determining variables $e_{M,k}$, A_k^M , $S_{M,k}$ and $K_k(1:M,:)$ by expression (43),

the processing section includes a step of updating the matrix G_k^N by expression (44) and calculating an auxiliary gain matrix $K_k^{U,N}$ as in expression (42),

15 the processing section includes a step of partitioning the auxiliary gain matrix $K_k^{U,N}$ by expression (41),

the processing section includes a step of calculating a variable D_k^M and a backward prediction error $\eta_{M,k}$ by expression (40),

20 the processing section includes a step of calculating the gain matrix K_k by expression (39),

the processing section includes a step of updating the filter equation of a fast H_∞ filter by expression (38), and

the processing section includes a step of advancing the
25 time k and repeating the respective steps.

5. The system identification device according to claim 1, wherein at the step of calculation by expression (44), a processing section of the filter obtains variables $e_{M,k-N+M-1}$,
30 $A_{k-N+M-1}^M$, $S_{M,k-N+M-1}$, $K_{k-N+M-1}^{U,M-1}(= K_{k-n+M-1}^M = K_{k-N+M-1}(1:M,:))$ by one

of followings:

1) values of the variables obtained at the respective steps are held on a memory during N-M steps, and

2) values of the variables at a time $t_{k-N+M-1}$ are also again
5 calculated at the respective steps.

6. The system identification device according to claim 1, wherein

the filter is applied to obtain a state estimated value
10 $\hat{x}_{k|k}$,

a pseudo-echo $\hat{d}_k$ is estimated as in a following expression, and this is subtracted from an echo to cancel the echo,

[Mathematical Expression 7]

$$\hat{d}_k = \sum_{i=0}^{N-1} \hat{h}_i[k] u_{k-i}, \quad k = 0, 1, 2, \dots \quad (49)$$

where,

$$\hat{x}_{k|k} = [\hat{h}_0[k], \dots, \hat{h}_{N-1}[k]]^T,$$

u_k and y_k respectively denote observed values of a received signal and the echo at the time t_k ($= kT$; T is a sampling period),
20 v_k denotes circuit noise having a mean value of 0 at the time t_k , and

N denotes the tap number (known).

7. A system identification method for performing fast
25 real-time identification of a time invariable or time variable system, by using:

a filter that is robust against a disturbance by determining that a maximum energy gain to a filter error from the disturbance, as an evaluation criterion, is restricted to

be smaller than a previously given upper limit γ_f^2 ,

wherein

the filter satisfies an H_∞ evaluation criterion as indicated by following expression (14) with respect to a state
5 space model as indicated by following expressions (11) to (13),

when an input signal is expressed by an $M(\leq N)$ -th order autoregressive model (AR model), the filter is given by following expressions (38) to (44), and

the filter satisfies a scalar existence condition of
10 following expressions (45) and (46):

[Mathematical Expression 1]

$$\mathbf{x}_{k+1} = \mathbf{x}_k + \mathbf{G}_k \mathbf{w}_k, \quad \mathbf{w}_k, \mathbf{x}_k \in \mathcal{R}^N \quad (11)$$

$$y_k = \mathbf{H}_k \mathbf{x}_k + v_k, \quad y_k, v_k \in \mathcal{R} \quad (12)$$

$$z_k = \mathbf{H}_k \mathbf{x}_k, \quad z_k \in \mathcal{R}, \mathbf{H}_k \in \mathcal{R}^{1 \times N} \quad (13)$$

$$\sup_{\mathbf{x}_0, \{\mathbf{w}_i\}, \{v_i\}} \frac{\sum_{i=0}^k \|e_{f,i}\|^2 / \rho}{\|\mathbf{x}_0 - \tilde{\mathbf{x}}_0\|_{\Sigma_0^{-1}}^2 + \sum_{i=0}^k \|\mathbf{w}_i\|^2 + \sum_{i=0}^k \|v_i\|^2 / \rho} < \gamma_f^2 \quad (14)$$

[Mathematical Expression 2]

$$\hat{\mathbf{x}}_{k|k} = \hat{\mathbf{x}}_{k-1|k-1} + \mathbf{K}_{s,k} (y_k - \mathbf{H}_k \hat{\mathbf{x}}_{k-1|k-1}) \quad (38)$$

$$\mathbf{K}_{s,k} = \frac{\mathbf{K}_k(:, 1)}{1 + \gamma_f^{-2} \mathbf{H}_k \mathbf{K}_k(:, 1)} \in \mathcal{R}^{N \times 1}$$

$$\mathbf{K}_k = \mathbf{m}_k - \mathbf{D}_k \boldsymbol{\mu}_k, \quad \mathbf{D}_k = \begin{bmatrix} \mathbf{0}_{N-M} \\ \mathbf{D}_k^M \end{bmatrix} \quad (39)$$

$$\mathbf{D}_k^M = \frac{\mathbf{D}_{k-1}^M - \mathbf{m}_k(N-M+1:N, :) \mathbf{W} \boldsymbol{\eta}_{M,k}}{1 - \boldsymbol{\mu}_k \mathbf{W} \boldsymbol{\eta}_{M,k}}$$

$$\boldsymbol{\eta}_{M,k} = \mathbf{c}_{k-N} + \mathbf{C}_k^M \mathbf{D}_{k-1}^M \quad (40)$$

$$\begin{bmatrix} \mathbf{m}_k \\ \boldsymbol{\mu}_k \end{bmatrix} = \check{\mathbf{K}}_k^N, \quad \mathbf{m}_k \in \mathcal{R}^{N \times 2}, \quad \boldsymbol{\mu}_k \in \mathcal{R}^{1 \times 2} \quad (41)$$

$$\check{\mathbf{K}}_k^N = \begin{bmatrix} \mathbf{0}_{(N-M+1) \times 2} \\ \check{\mathbf{K}}_{k-N+M-1}^{M-1} \end{bmatrix} + \mathbf{G}_k^N, \quad \check{\mathbf{K}}_{k-N+M-1}^{M-1} = \mathbf{K}_{k-N+M-1}(1:M, :) \quad (42)$$

$$\begin{aligned} S_{M,k} &= \rho S_{M,k-1} + \mathbf{e}_{M,k}^T \mathbf{W} \tilde{\mathbf{e}}_{M,k}, \quad \mathbf{e}_{M,k} = \mathbf{c}_k + \mathbf{C}_{k-1}^M \mathbf{A}_k^M \\ \mathbf{A}_k^M &= \mathbf{A}_{k-1}^M - \mathbf{K}_{k-1}(1:M, :) \mathbf{W} \tilde{\mathbf{e}}_{M,k}, \quad \tilde{\mathbf{e}}_{M,k} = \mathbf{c}_k + \mathbf{C}_{k-1}^M \mathbf{A}_{k-1}^M \end{aligned} \quad (43)$$

15

here, $\mathbf{G}_k^N$ is updated as follows:

$$\begin{aligned} \begin{bmatrix} \mathbf{G}_k^N \\ \mathbf{0}_{1 \times 2} \end{bmatrix} &= \begin{bmatrix} \mathbf{0}_{1 \times 2} \\ \mathbf{G}_{k-1}^N \end{bmatrix} + \begin{bmatrix} \mathbf{e}_{M,k}^T / S_{M,k} \\ \mathbf{A}_k^M \mathbf{e}_{M,k}^T / S_{M,k} \\ \mathbf{0}_{(N-M+1) \times 2} \end{bmatrix} \\ &\quad - \begin{bmatrix} \mathbf{0}_{(N-M+1) \times 2} \\ \mathbf{e}_{M,k-N+M-1}^T / S_{M,k-N+M-1} \\ \mathbf{A}_{k-N+M-1}^M \mathbf{e}_{M,k-N+M-1}^T / S_{M,k-N+M-1} \end{bmatrix} \end{aligned} \quad (44)$$

where,

$$\mathbf{C}_k(:, N-M+1:N), \mathbf{C}_{k-1}^M = \mathbf{C}_{k-1}(:, 1:M), \mathbf{C}_k = \begin{bmatrix} \mathbf{H}_k \\ \mathbf{H}_k \end{bmatrix}, \quad \mathbf{W} = \begin{bmatrix} 1 & 0 \\ 0 & -\gamma_f^{-2} \end{bmatrix}$$

$$\mathbf{e}_{f,i} = \mathbf{z}_{i|i}^v - \mathbf{H}_i \mathbf{x}_i, \quad \mathbf{z}_{i|i}^v = \mathbf{H}_i \hat{\mathbf{x}}_{i|i}$$

5 $(\mathbf{c}_k \in \mathbb{R}^{2 \times 1}$ is a first column vector of $\mathbf{C}_k = [\mathbf{c}_k, \dots, \mathbf{c}_{k-N+1}]$,
 $\mathbf{c}_{k-1} = \mathbf{0}_{2 \times 1}$ and $k-i < 0$ are assumed, and initial values are set
to be $\mathbf{K}_0 = \mathbf{0}_{N \times 2}$, $\mathbf{G}_0^N = \mathbf{0}_{(N+1) \times 2}$, $\mathbf{A}_0^M = \mathbf{0}_{M \times 1}$, $S_{M,0} = 1/\epsilon_0$, $\mathbf{D}_0^M = \mathbf{0}_{M \times 1}$,
 $\hat{\mathbf{x}}_{0|0} = \mathbf{x}^v_0 = \mathbf{0}_{N \times 1}$, here, $\mathbf{0}_{m \times n}$ denotes an $m \times n$ zero matrix)
[Mathematical Expression 3]

$$10 \quad -\varrho \hat{\Xi}_i + \rho \gamma_f^2 > 0, \quad i = 0, \dots, k \quad (45)$$

here, $\varrho, \hat{\Xi}_i$ are respectively defined by following expressions:

$$\varrho = 1 - \gamma_f^2, \quad \hat{\Xi}_i = \frac{\rho \mathbf{H}_i \mathbf{K}_{s,i}}{1 - \mathbf{H}_i \mathbf{K}_{s,i}} = \frac{\rho \mathbf{H}_i \mathbf{K}_i(:, 1)}{1 - (1 - \gamma_f^{-2}) \mathbf{H}_i \mathbf{K}_i(:, 1)} \quad (46)$$

where

$\mathbf{x}_k$: a state vector or simply a state; unknown, this is an object
15 of estimation,
 $\mathbf{x}_0$: an initial state; unknown,
 $\mathbf{w}_k$: a system noise; unknown,
 $\mathbf{v}_k$: an observation noise; unknown,
 $\mathbf{y}_k$: an observation signal; input of the filter and known,
20 $\mathbf{z}_k$: an output signal, unknown,
 $\mathbf{G}_k$: a drive matrix; becomes known at execution,
 $\mathbf{H}_k$: an observation matrix; known,
 $\hat{\mathbf{x}}_{k|k}$: an estimated value of the state $\mathbf{x}_k$ at a time k using

observation signals $y_0 - y_k$; given by a filter equation,
 $K_{s,k}$: a filter gain; obtained from a gain matrix K_k ,
 ρ : a forgetting factor; in a case of Theorem 1 - Theorem 3,
 when γ_f is determined, it is automatically determined by $\rho =$

5 $1 - \chi(\gamma_f),$

Σ_0^{-1} : an inverse matrix of a weighting matrix expressing
 uncertainty of a state; Σ_0 is known,

N : a dimension (tap number) of a state vector; previously given,

M : an order of an AR model; previously given,

10 μ_k : $N+1$ th row vector of $K_k^{U\ N}$; obtained from $K_k^{U\ N}$,

m_k : $N \times 2$ matrix including a first to an N -th row of $K_k^{U\ N}$; obtained
 from $K_k^{U\ N}$,

γ_f : attenuation level; given at design time

D_k^M : a backward prediction coefficient vector; obtained from

15 $m_k, \eta_{M,k}$ and μ_k ,

W : a weighting matrix; determined from γ_f ,

A_k^M : a forward prediction coefficient vector; obtained from K_{k-1}
 and $\tilde{e}_{M,k}$,

20 C_k^M : a $2 \times M$ matrix including a 1st to an M -th column vector of
 C_k ; determined from the observation matrix H_k , and

$\underline{C}_k^M$: a $2 \times M$ matrix including an $N-M+1$ -th to an N -th column vector
 of C_k ; determined from the observation matrix H_k .

8. A computer readable recording medium recording a
 25 system identification program that causes a computer to perform
 fast real-time identification of a time invariable or time
 variable system, by using:

a filter that is robust against a disturbance by
 determining that a maximum energy gain to a filter error from
 30 the disturbance, as an evaluation criterion, is restricted to

be smaller than a previously given upper limit γ_f^2 ,

wherein

the filter satisfies an H_∞ evaluation criterion as indicated by following expression (14) with respect to a state

5 space model as indicated by following expressions (11) to (13),

when an input signal is expressed by an $M(\leq N)$ -th order autoregressive model (AR model), the filter is given by following expressions (38) to (44), and

the filter satisfies a scalar existence condition of following expressions (45) and (46):

[Mathematical Expression 1]

$$\mathbf{x}_{k+1} = \mathbf{x}_k + \mathbf{G}_k \mathbf{w}_k, \quad \mathbf{w}_k, \mathbf{x}_k \in \mathcal{R}^N \quad (11)$$

$$y_k = \mathbf{H}_k \mathbf{x}_k + v_k, \quad y_k, v_k \in \mathcal{R} \quad (12)$$

$$z_k = \mathbf{H}_k \mathbf{x}_k, \quad z_k \in \mathcal{R}, \quad \mathbf{H}_k \in \mathcal{R}^{1 \times N} \quad (13)$$

$$\sup_{\mathbf{x}_0, \{\mathbf{w}_i\}, \{v_i\}} \frac{\sum_{i=0}^k \|e_{f,i}\|^2 / \rho}{\|\mathbf{x}_0 - \check{\mathbf{x}}_0\|_{\Sigma_0^{-1}}^2 + \sum_{i=0}^k \|\mathbf{w}_i\|^2 + \sum_{i=0}^k \|v_i\|^2 / \rho} < \gamma_f^2 \quad (14)$$

[Mathematical Expression 2]

$$\hat{\mathbf{x}}_{k|k} = \hat{\mathbf{x}}_{k-1|k-1} + \mathbf{K}_{s,k} (y_k - \mathbf{H}_k \hat{\mathbf{x}}_{k-1|k-1}) \quad (38)$$

$$\mathbf{K}_{s,k} = \frac{\mathbf{K}_k(:, 1)}{1 + \gamma_f^{-2} \mathbf{H}_k \mathbf{K}_k(:, 1)} \in \mathcal{R}^{N \times 1}$$

$$\mathbf{K}_k = \mathbf{m}_k - \mathbf{D}_k \boldsymbol{\mu}_k, \quad \mathbf{D}_k = \begin{bmatrix} \mathbf{0}_{N-M} \\ \mathbf{D}_k^M \end{bmatrix} \quad (39)$$

$$\mathbf{D}_k^M = \frac{\mathbf{D}_{k-1}^M - \mathbf{m}_k(N-M+1:N, :) \mathbf{W} \boldsymbol{\eta}_{M,k}}{1 - \boldsymbol{\mu}_k \mathbf{W} \boldsymbol{\eta}_{M,k}}$$

$$\boldsymbol{\eta}_{M,k} = \mathbf{c}_{k-N} + \mathbf{C}_k^M \mathbf{D}_{k-1}^M \quad (40)$$

$$\begin{bmatrix} \mathbf{m}_k \\ \boldsymbol{\mu}_k \end{bmatrix} = \check{\mathbf{K}}_k^N, \quad \mathbf{m}_k \in \mathcal{R}^{N \times 2}, \quad \boldsymbol{\mu}_k \in \mathcal{R}^{1 \times 2} \quad (41)$$

$$\check{\mathbf{K}}_k^N = \begin{bmatrix} \mathbf{0}_{(N-M+1) \times 2} \\ \check{\mathbf{K}}_{k-N+M-1}^{M-1} \end{bmatrix} + \mathbf{G}_k^N, \quad \check{\mathbf{K}}_{k-N+M-1}^{M-1} = \mathbf{K}_{k-N+M-1}(1:M, :) \quad (42)$$

$$\begin{aligned} S_{M,k} &= \rho S_{M,k-1} + \mathbf{e}_{M,k}^T \mathbf{W} \tilde{\mathbf{e}}_{M,k}, \quad \mathbf{e}_{M,k} = \mathbf{c}_k + \mathbf{C}_{k-1}^M \mathbf{A}_k^M \\ \mathbf{A}_k^M &= \mathbf{A}_{k-1}^M - \mathbf{K}_{k-1}(1:M, :) \mathbf{W} \tilde{\mathbf{e}}_{M,k}, \quad \tilde{\mathbf{e}}_{M,k} = \mathbf{c}_k + \mathbf{C}_{k-1}^M \mathbf{A}_{k-1}^M \end{aligned} \quad (43)$$

15

here, $\mathbf{G}_k^N$ is updated as follows:

$$\begin{bmatrix} \mathbf{G}_k^N \\ \mathbf{0}_{1 \times 2} \end{bmatrix} = \begin{bmatrix} \mathbf{0}_{1 \times 2} \\ \mathbf{G}_{k-1}^N \end{bmatrix} + \begin{bmatrix} \mathbf{e}_{M,k}^T / S_{M,k} \\ \mathbf{A}_k^M \mathbf{e}_{M,k}^T / S_{M,k} \\ \mathbf{0}_{(N-M+1) \times 2} \end{bmatrix} - \begin{bmatrix} \mathbf{0}_{(N-M+1) \times 2} \\ \mathbf{e}_{M,k-N+M-1}^T / S_{M,k-N+M-1} \\ \mathbf{A}_{k-N+M-1}^M \mathbf{e}_{M,k-N+M-1}^T / S_{M,k-N+M-1} \end{bmatrix} \quad (44)$$

where,

$$\mathbf{C}_k(:, N-M+1:N), \mathbf{C}_{k-1}^M = \mathbf{C}_{k-1}(:, 1:M), \mathbf{C}_k = \begin{bmatrix} \mathbf{H}_k \\ \mathbf{H}_k \end{bmatrix}, \quad \mathbf{W} = \begin{bmatrix} 1 & 0 \\ 0 & -\gamma_f^{-2} \end{bmatrix}$$

$$\mathbf{e}_{f,i} = \mathbf{z}_{i|i}^v - \mathbf{H}_i \mathbf{x}_i, \quad \mathbf{z}_{i|i}^v = \mathbf{H}_i \hat{\mathbf{x}}_{i|i}$$

5 $(\mathbf{c}_k \in \mathbb{R}^{2 \times 1}$ is a first column vector of $\mathbf{C}_k = [\mathbf{c}_k, \dots, \mathbf{c}_{k-N+1}]$, $\mathbf{c}_{k-1} = \mathbf{0}_{2 \times 1}$ and $k-i < 0$ are assumed, and initial values are set to be $\mathbf{K}_0 = \mathbf{0}_{N \times 2}$, $\mathbf{G}_0^N = \mathbf{0}_{(N+1) \times 2}$, $\mathbf{A}_0^M = \mathbf{0}_{M \times 1}$, $S_{M,0} = 1/\epsilon_0$, $\mathbf{D}_0^M = \mathbf{0}_{M \times 1}$, $\hat{\mathbf{x}}_{0|0} = \mathbf{x}^v_0 = \mathbf{0}_{N \times 1}$, here, $\mathbf{0}_{m \times n}$ denotes an $m \times n$ zero matrix)
[Mathematical Expression 3]

$$-\varrho \hat{\Xi}_i + \rho \gamma_f^2 > 0, \quad i = 0, \dots, k \quad (45)$$

here, $\varrho, \hat{\Xi}_i$ are respectively defined by following expressions:

$$\varrho = 1 - \gamma_f^2, \quad \hat{\Xi}_i = \frac{\rho \mathbf{H}_i \mathbf{K}_{s,i}}{1 - \mathbf{H}_i \mathbf{K}_{s,i}} = \frac{\rho \mathbf{H}_i \mathbf{K}_i(:, 1)}{1 - (1 - \gamma_f^{-2}) \mathbf{H}_i \mathbf{K}_i(:, 1)} \quad (46)$$

where

$\mathbf{x}_k$: a state vector or simply a state; unknown, this is an object

15 of estimation,

$\mathbf{x}_0$: an initial state; unknown,

$\mathbf{w}_k$: a system noise; unknown,

$\mathbf{v}_k$: an observation noise; unknown,

$\mathbf{y}_k$: an observation signal; input of the filter and known,

20 $\mathbf{z}_k$: an output signal, unknown,

$\mathbf{G}_k$: a drive matrix; becomes known at execution,

$\mathbf{H}_k$: an observation matrix; known,

$\hat{\mathbf{x}}_{k|k}$: an estimated value of the state $\mathbf{x}_k$ at a time k using

observation signals $y_0 - y_k$; given by a filter equation,
 $K_{s,k}$: a filter gain; obtained from a gain matrix K_k ,
 ρ : a forgetting factor; in a case of Theorem 1 - Theorem 3,
 when γ_f is determined, it is automatically determined by $\rho =$
 5 $1 - \chi(\gamma_f)$,
 Σ_0^{-1} : an inverse matrix of a weighting matrix expressing
 uncertainty of a state; Σ_0 is known,
 N : a dimension (tap number) of a state vector; previously given,
 M : an order of an AR model; previously given,
 10 μ_k : $N+1$ th row vector of $K_k^{U N}$; obtained from $K_k^{U N}$,
 m_k : $N \times 2$ matrix including a first to an N -th row of $K_k^{U N}$; obtained
 from $K_k^{U N}$,
 γ_f : attenuation level; given at design time
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 C_k^M : a $2 \times M$ matrix including a 1st to an M -th column vector of
 20 C_k ; determined from the observation matrix H_k , and
 $\underline{C}_k^M$: a $2 \times M$ matrix including an $N-M+1$ -th to an N -th column vector
 of C_k ; determined from the observation matrix H_k .

9. A system identification program that causes a
 25 computer to perform fast real-time identification of a time
 invariable or time variable system, by using:

a filter that is robust against a disturbance by
 determining that a maximum energy gain to a filter error from
 the disturbance, as an evaluation criterion, is restricted to
 30 be smaller than a previously given upper limit γ_f^2 ,

wherein

the filter satisfies an H_∞ evaluation criterion as indicated by following expression (14) with respect to a state space model as indicated by following expressions (11) to (13),

5 when an input signal is expressed by an $M(\leq N)$ -th order autoregressive model (AR model), the filter is given by following expressions (38) to (44), and

the filter satisfies a scalar existence condition of following expressions (45) and (46):

10 [Mathematical Expression 1]

$$\mathbf{x}_{k+1} = \mathbf{x}_k + \mathbf{G}_k \mathbf{w}_k, \quad \mathbf{w}_k, \mathbf{x}_k \in \mathcal{R}^N \quad (11)$$

$$y_k = \mathbf{H}_k \mathbf{x}_k + v_k, \quad y_k, v_k \in \mathcal{R} \quad (12)$$

$$z_k = \mathbf{H}_k \mathbf{x}_k, \quad z_k \in \mathcal{R}, \mathbf{H}_k \in \mathcal{R}^{1 \times N} \quad (13)$$

$$\sup_{x_0, \{w_i\}, \{v_i\}} \frac{\sum_{i=0}^k \|e_{f,i}\|^2 / \rho}{\|\mathbf{x}_0 - \tilde{\mathbf{x}}_0\|_{\Sigma_0^{-1}}^2 + \sum_{i=0}^k \|\mathbf{w}_i\|^2 + \sum_{i=0}^k \|v_i\|^2 / \rho} < \gamma_f^2 \quad (14)$$

[Mathematical Expression 2]

$$\hat{\mathbf{x}}_{k|k} = \hat{\mathbf{x}}_{k-1|k-1} + \mathbf{K}_{s,k} (y_k - \mathbf{H}_k \hat{\mathbf{x}}_{k-1|k-1}) \quad (38)$$

$$\mathbf{K}_{s,k} = \frac{\mathbf{K}_k(:, 1)}{1 + \gamma_f^{-2} \mathbf{H}_k \mathbf{K}_k(:, 1)} \in \mathcal{R}^{N \times 1}$$

$$\mathbf{K}_k = \mathbf{m}_k - \mathbf{D}_k \boldsymbol{\mu}_k, \quad \mathbf{D}_k = \begin{bmatrix} \mathbf{0}_{N-M} \\ \mathbf{D}_k^M \end{bmatrix} \quad (39)$$

$$\mathbf{D}_k^M = \frac{\mathbf{D}_{k-1}^M - \mathbf{m}_k(N-M+1:N, :) \mathbf{W} \boldsymbol{\eta}_{M,k}}{1 - \boldsymbol{\mu}_k \mathbf{W} \boldsymbol{\eta}_{M,k}}$$

$$\boldsymbol{\eta}_{M,k} = \mathbf{c}_{k-N} + \mathbf{C}_k^M \mathbf{D}_{k-1}^M \quad (40)$$

$$\begin{bmatrix} \mathbf{m}_k \\ \boldsymbol{\mu}_k \end{bmatrix} = \check{\mathbf{K}}_k^N, \quad \mathbf{m}_k \in \mathcal{R}^{N \times 2}, \quad \boldsymbol{\mu}_k \in \mathcal{R}^{1 \times 2} \quad (41)$$

$$\check{\mathbf{K}}_k^N = \begin{bmatrix} \mathbf{0}_{(N-M+1) \times 2} \\ \check{\mathbf{K}}_{k-N+M-1}^{M-1} \end{bmatrix} + \mathbf{G}_k^N, \quad \check{\mathbf{K}}_{k-N+M-1}^{M-1} = \mathbf{K}_{k-N+M-1}(1:M, :) \quad (42)$$

$$\begin{aligned} S_{M,k} &= \rho S_{M,k-1} + \mathbf{e}_{M,k}^T \mathbf{W} \tilde{\mathbf{e}}_{M,k}, \quad \mathbf{e}_{M,k} = \mathbf{c}_k + \mathbf{C}_{k-1}^M \mathbf{A}_k^M \\ \mathbf{A}_k^M &= \mathbf{A}_{k-1}^M - \mathbf{K}_{k-1}(1:M, :) \mathbf{W} \tilde{\mathbf{e}}_{M,k}, \quad \tilde{\mathbf{e}}_{M,k} = \mathbf{c}_k + \mathbf{C}_{k-1}^M \mathbf{A}_{k-1}^M \end{aligned} \quad (43)$$

15 here, $\mathbf{G}_k^N$ is updated as follows:

$$\begin{aligned} \begin{bmatrix} \mathbf{G}_k^N \\ \mathbf{0}_{1 \times 2} \end{bmatrix} &= \begin{bmatrix} \mathbf{0}_{1 \times 2} \\ \mathbf{G}_{k-1}^N \end{bmatrix} + \begin{bmatrix} \mathbf{e}_{M,k}^T / S_{M,k} \\ \mathbf{A}_k^M \mathbf{e}_{M,k}^T / S_{M,k} \\ \mathbf{0}_{(N-M+1) \times 2} \end{bmatrix} \\ &\quad - \begin{bmatrix} \mathbf{0}_{(N-M+1) \times 2} \\ \mathbf{e}_{M,k-N+M-1}^T / S_{M,k-N+M-1} \\ \mathbf{A}_{k-N+M-1}^M \mathbf{e}_{M,k-N+M-1}^T / S_{M,k-N+M-1} \end{bmatrix} \end{aligned} \quad (44)$$

where,

$$\mathbf{C}_k(:, N-M+1:N), \mathbf{C}_{k-1}^M = \mathbf{C}_{k-1}(:, 1:M), \mathbf{C}_k = \begin{bmatrix} \mathbf{H}_k \\ \mathbf{H}_k \end{bmatrix}, \quad \mathbf{W} = \begin{bmatrix} 1 & 0 \\ 0 & -\gamma_f^{-2} \end{bmatrix}$$

$$\mathbf{e}_{f,i} = \mathbf{z}_{i|i}^v - \mathbf{H}_i \mathbf{x}_i, \quad \mathbf{z}_{i|i}^v = \mathbf{H}_i \hat{\mathbf{x}}_{i|i}$$

5 $(\mathbf{c}_k \in \mathbb{R}^{2 \times 1}$ is a first column vector of $\mathbf{C}_k = [\mathbf{c}_k, \dots, \mathbf{c}_{k-N+1}]$,
 $\mathbf{c}_{k-1} = \mathbf{0}_{2 \times 1}$ and $k-i < 0$ are assumed, and initial values are set
to be $\mathbf{K}_0 = \mathbf{0}_{N \times 2}$, $\mathbf{G}_0^N = \mathbf{0}_{(N+1) \times 2}$, $\mathbf{A}_0^M = \mathbf{0}_{M \times 1}$, $S_{M,0} = 1/\epsilon_0$, $\mathbf{D}_0^M = \mathbf{0}_{M \times 1}$,
 $\hat{\mathbf{x}}_{0|0} = \mathbf{x}^v_0 = \mathbf{0}_{N \times 1}$, here, $\mathbf{0}_{m \times n}$ denotes an $m \times n$ zero matrix)
[Mathematical Expression 3]

$$-\varrho \hat{\Xi}_i + \rho \gamma_f^2 > 0, \quad i=0, \dots, k \quad (45)$$

10

here, $\varrho, \hat{\Xi}_i$ are respectively defined by following expressions:

$$\varrho = 1 - \gamma_f^2, \quad \hat{\Xi}_i = \frac{\rho \mathbf{H}_i \mathbf{K}_{s,i}}{1 - \mathbf{H}_i \mathbf{K}_{s,i}} = \frac{\rho \mathbf{H}_i \mathbf{K}_i(:, 1)}{1 - (1 - \gamma_f^{-2}) \mathbf{H}_i \mathbf{K}_i(:, 1)} \quad (46)$$

where

$\mathbf{x}_k$: a state vector or simply a state; unknown, this is an object

15 of estimation,

$\mathbf{x}_0$: an initial state; unknown,

$\mathbf{w}_k$: a system noise; unknown,

$\mathbf{v}_k$: an observation noise; unknown,

$\mathbf{y}_k$: an observation signal; input of the filter and known,

20 $\mathbf{z}_k$: an output signal, unknown,

$\mathbf{G}_k$: a drive matrix; becomes known at execution,

$\mathbf{H}_k$: an observation matrix; known,

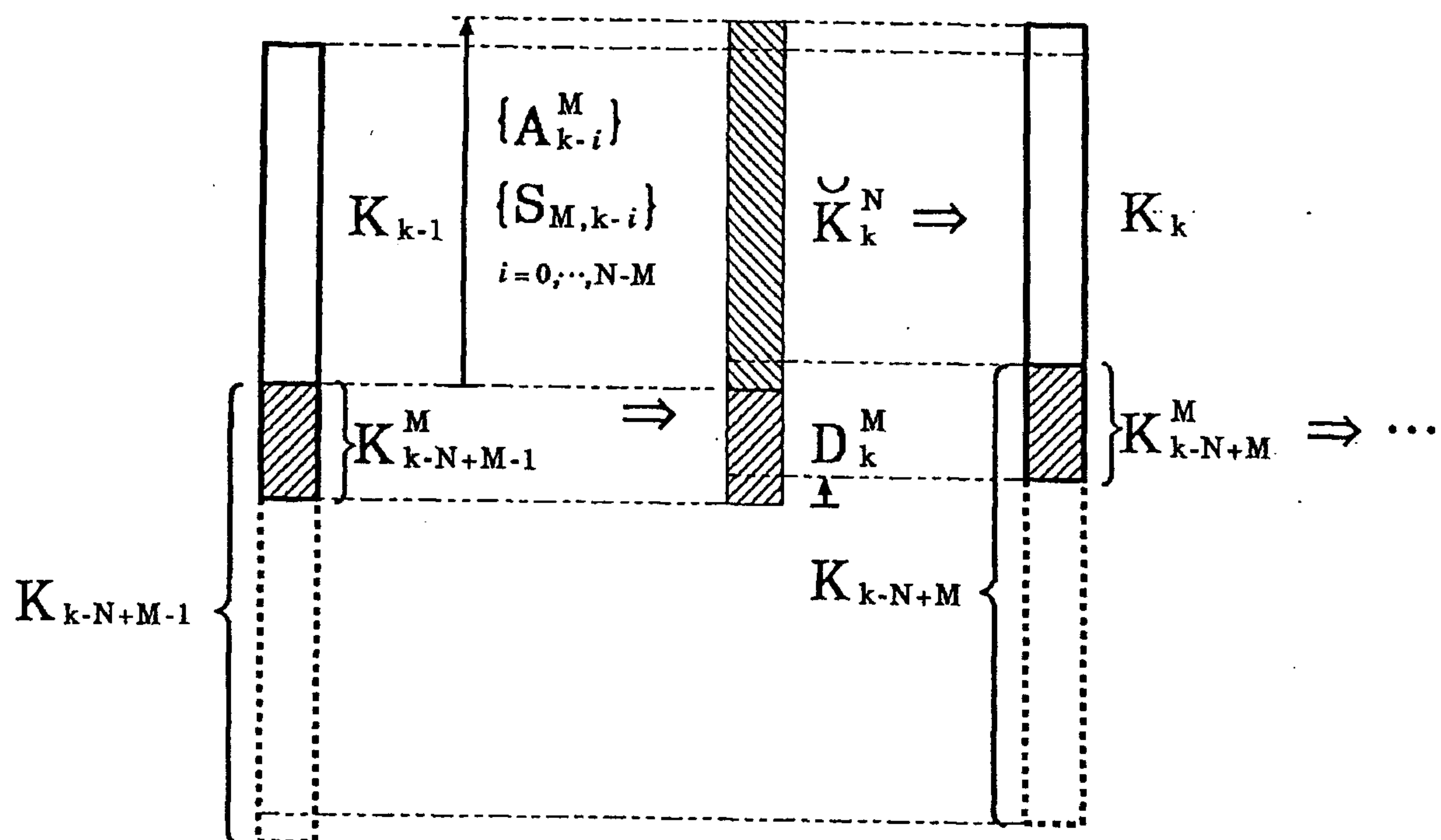
$\hat{\mathbf{x}}_{k|k}$: an estimated value of the state $\mathbf{x}_k$ at a time k using

observation signals $y_0 - y_k$; given by a filter equation,
 $K_{s,k}$: a filter gain; obtained from a gain matrix K_k ,
 ρ : a forgetting factor; in a case of Theorem 1 - Theorem 3,
 when γ_f is determined, it is automatically determined by $\rho =$
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 of C_k ; determined from the observation matrix H_k .

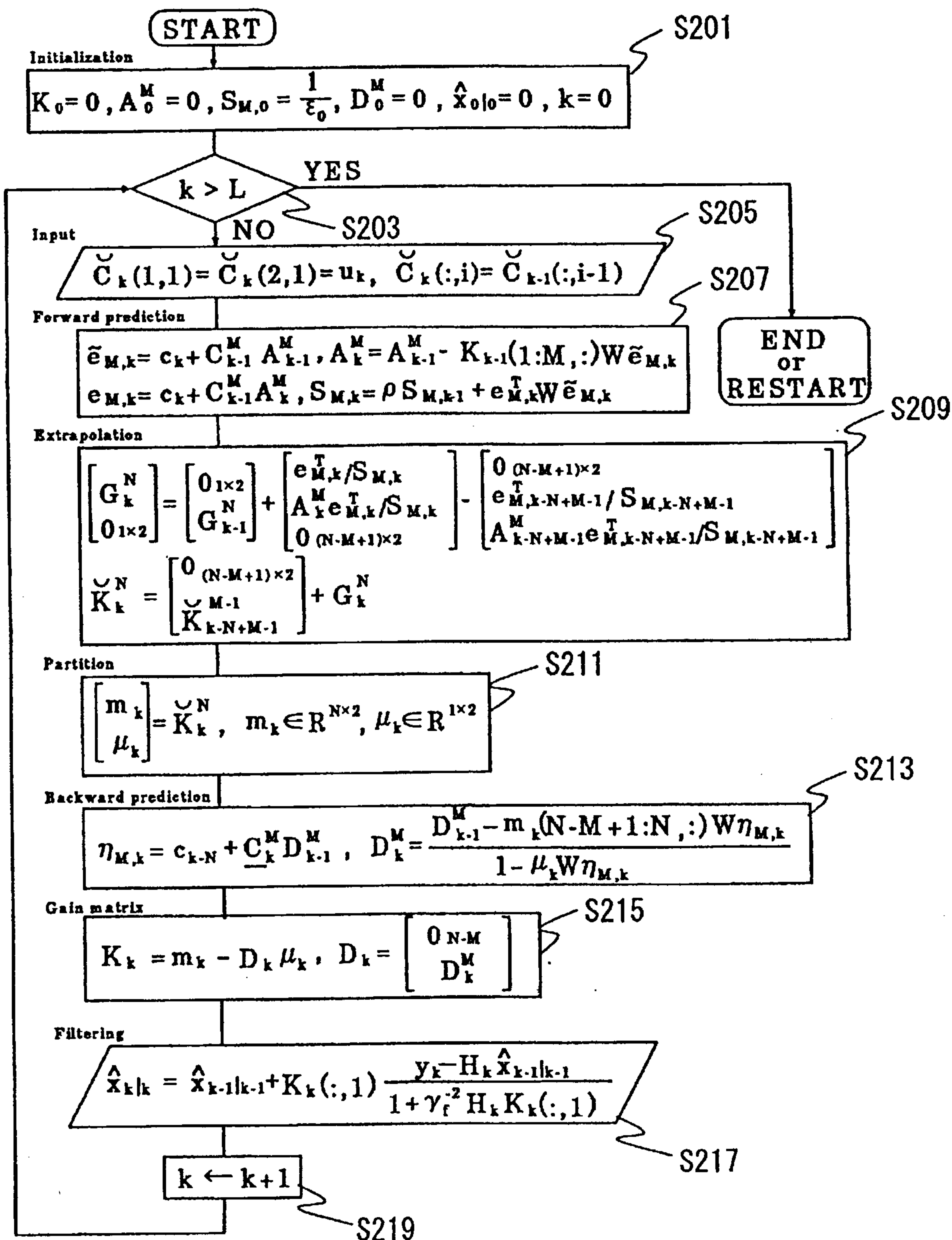
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[図1]



[図2]

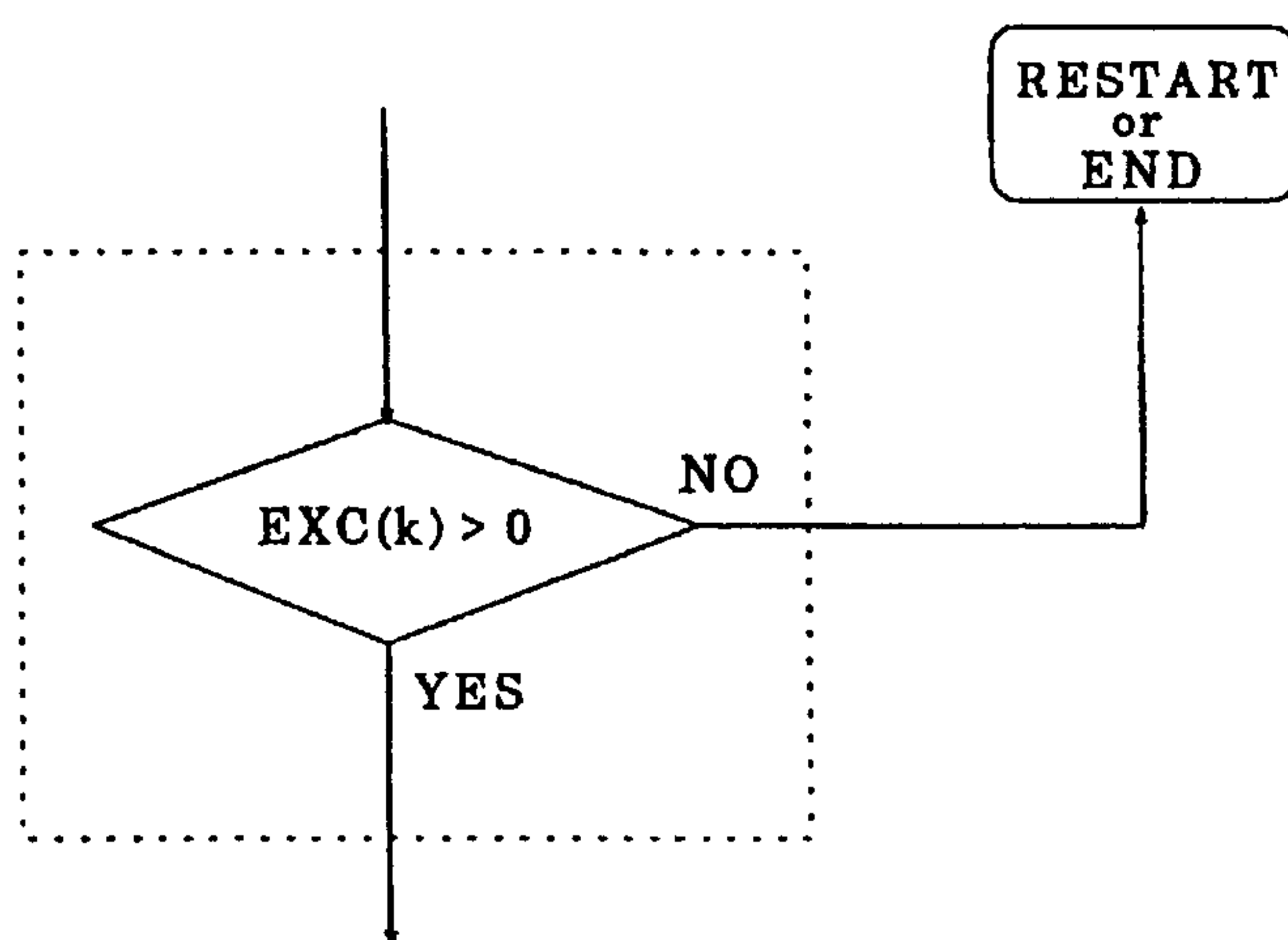


$$\underline{C}_k^M = \check{C}_k(:, N-M+1:N), C_{k-1}^M = \check{C}_k(:, 2:M+1), H_k = \check{C}_k(1, 1:N).$$

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[図3]

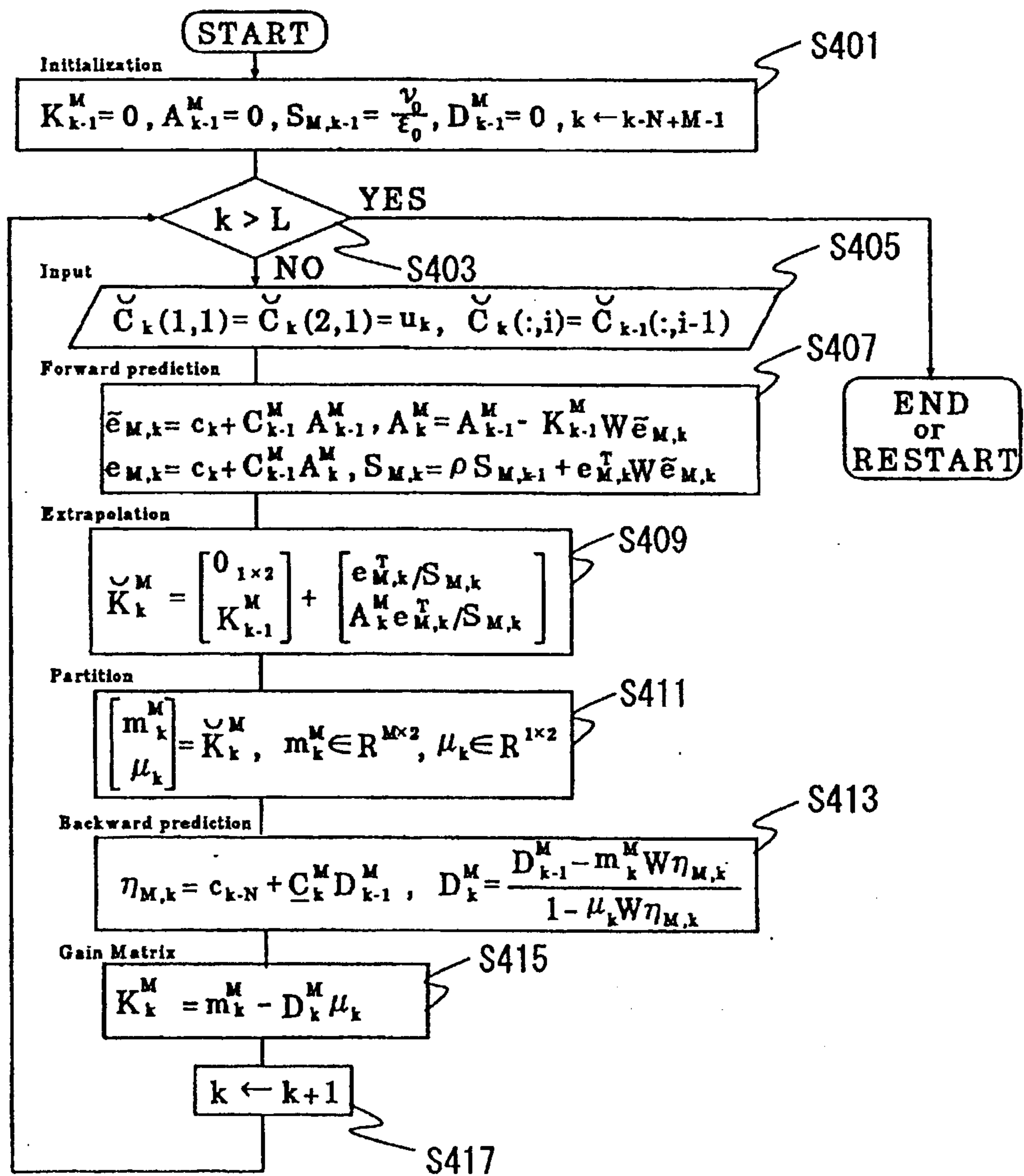


$$EXC(k) = -\rho \hat{\Xi}_k + \rho \gamma_f^2.$$

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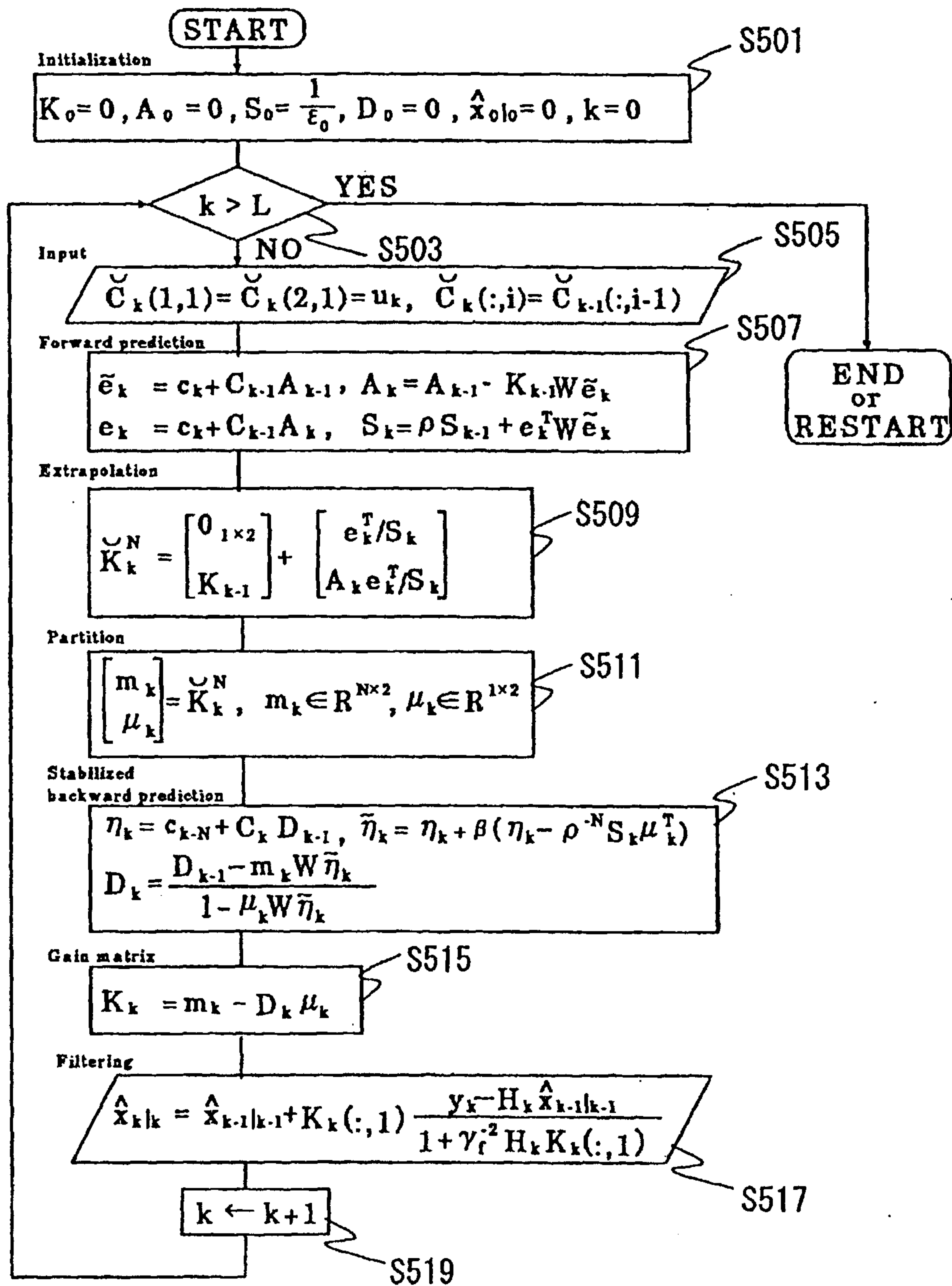
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[図4]



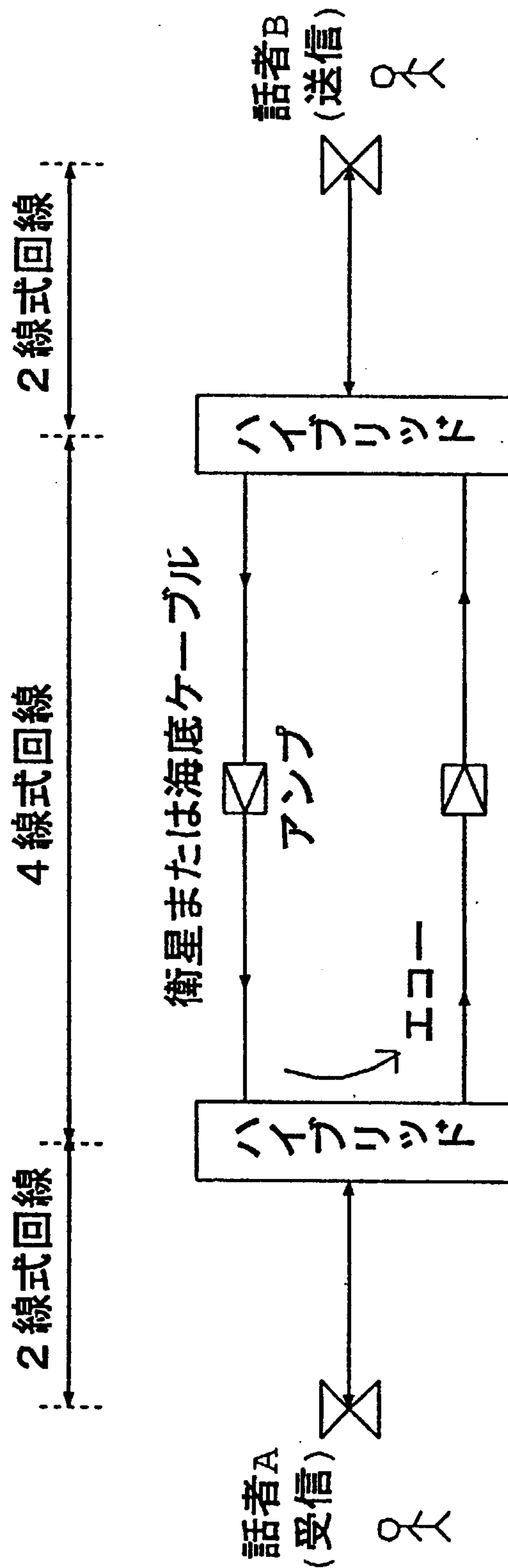
$$C_{k-1}^M = \check{C}_k(:, 2 : M+1), C_k^M = \check{C}_k(:, 1 : M).$$

[図5]



$$C_{k-1} = \check{C}_k(:, 2 : N+1), C_k = \check{C}_k(:, 1 : N), H_k = \check{C}_k(1, 1 : N).$$

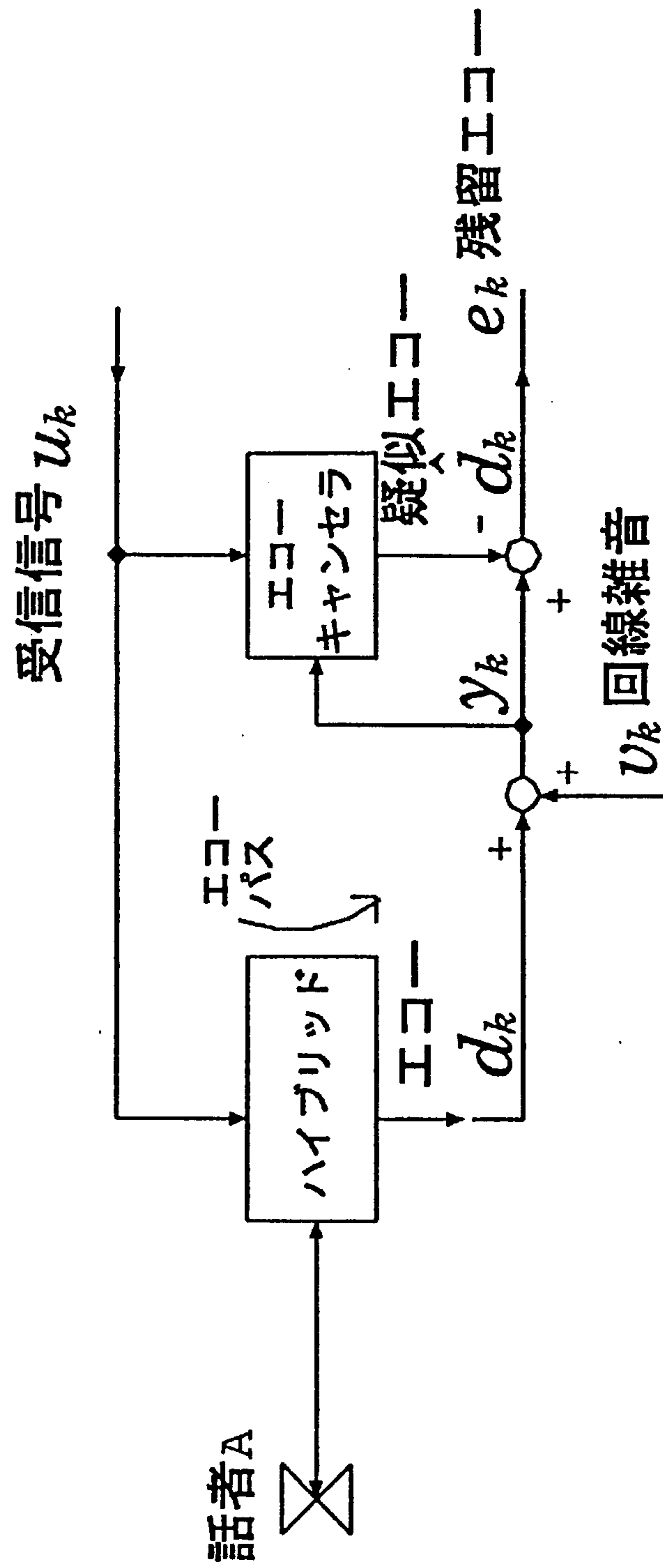
[図6]



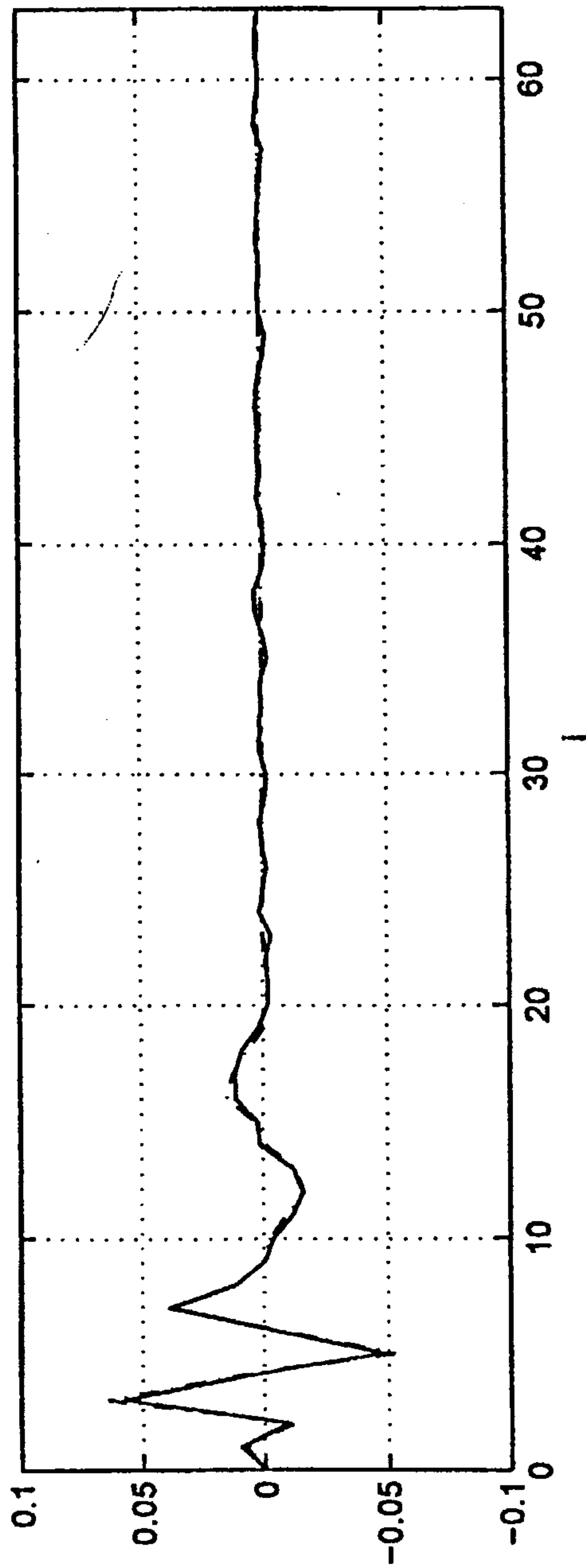
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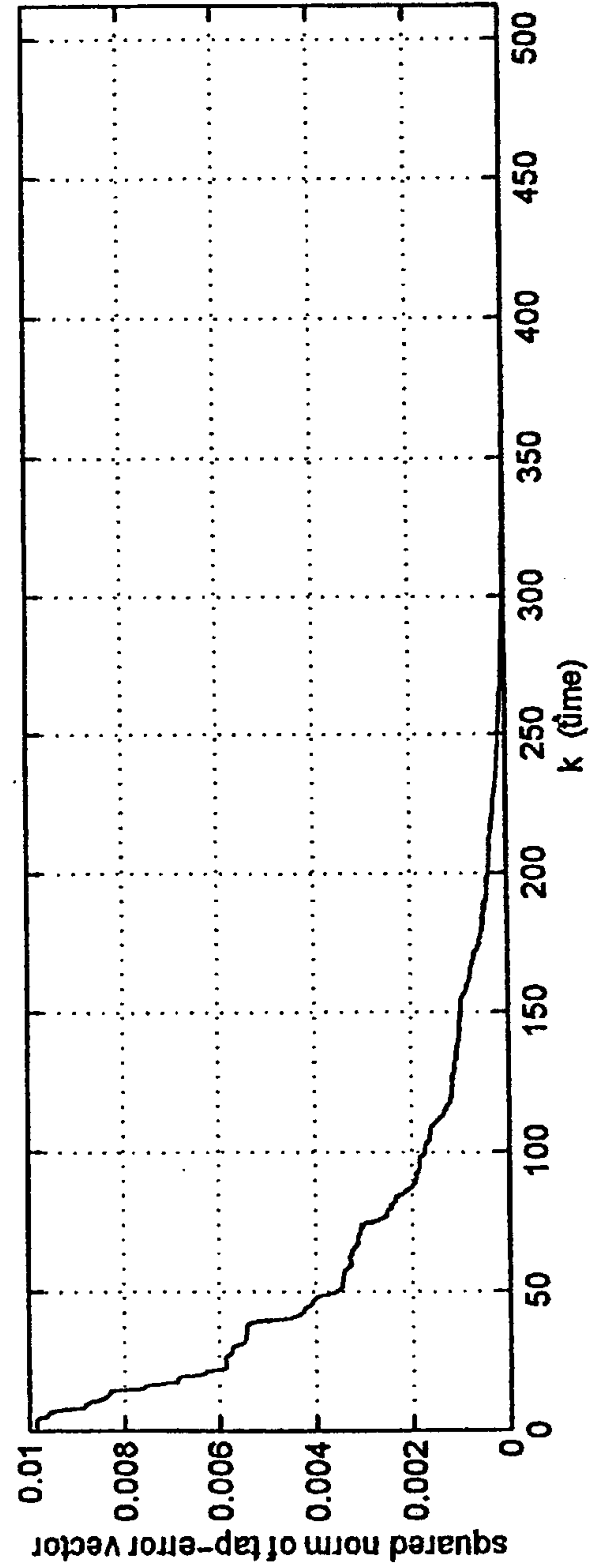
[図7]



[図8]



(a) インパルス応答の推定値 ($\hat{x}_{256|256}$)

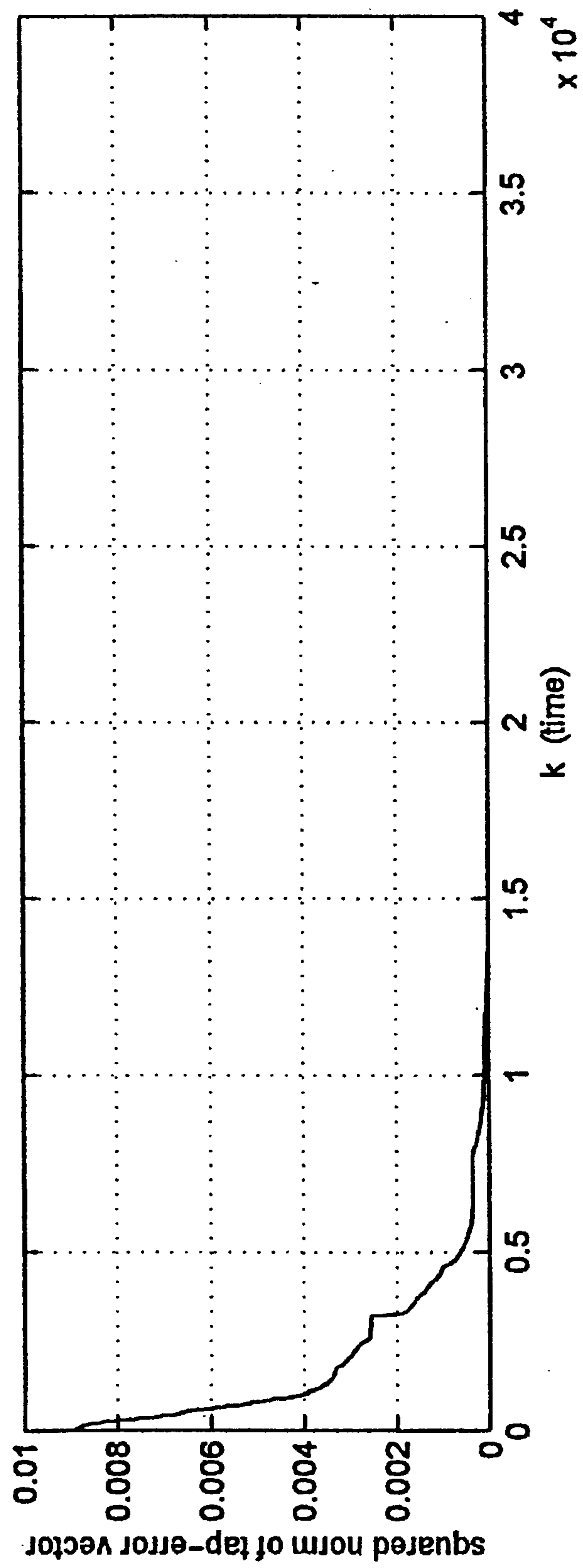


(b) タップ誤差の収束特性

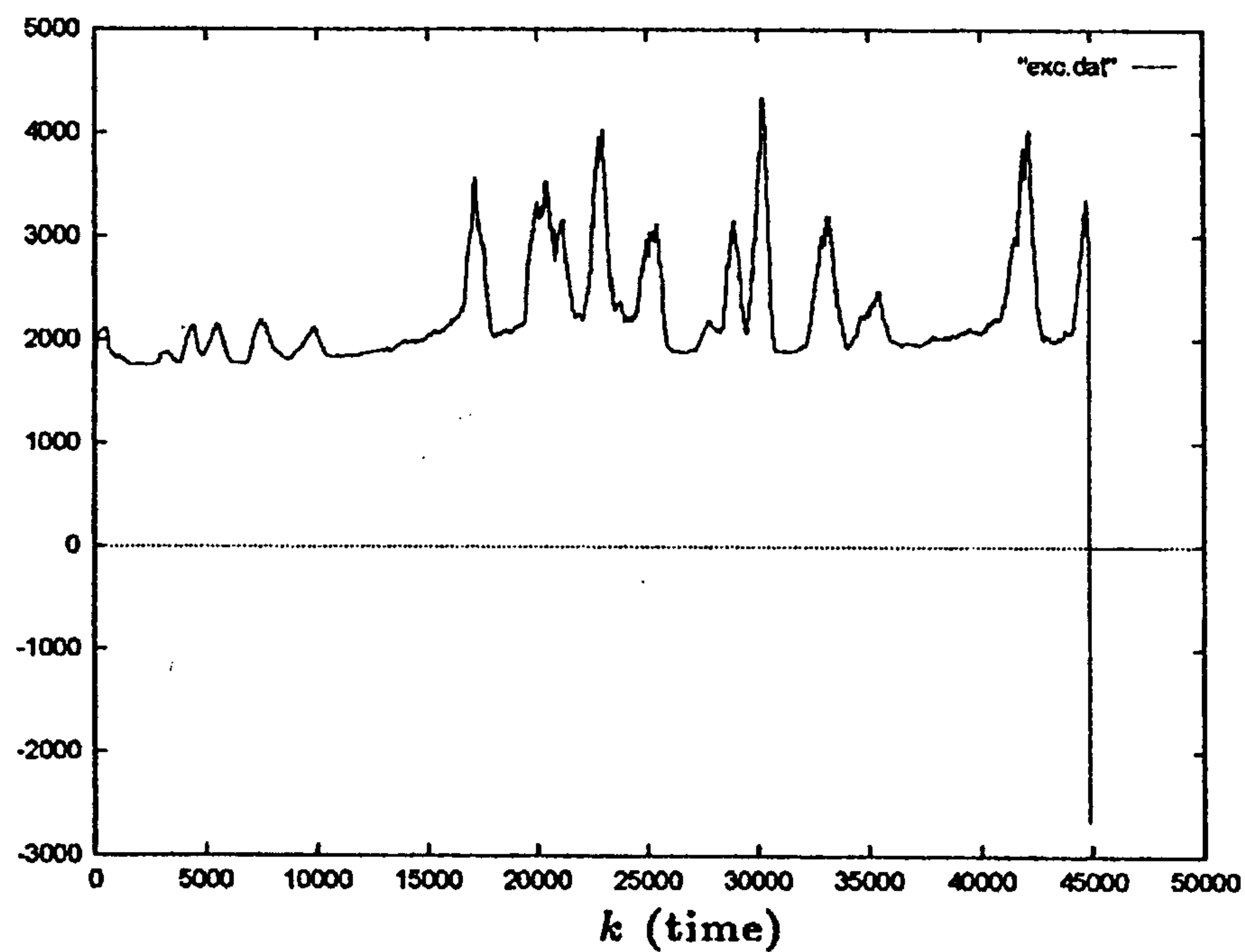
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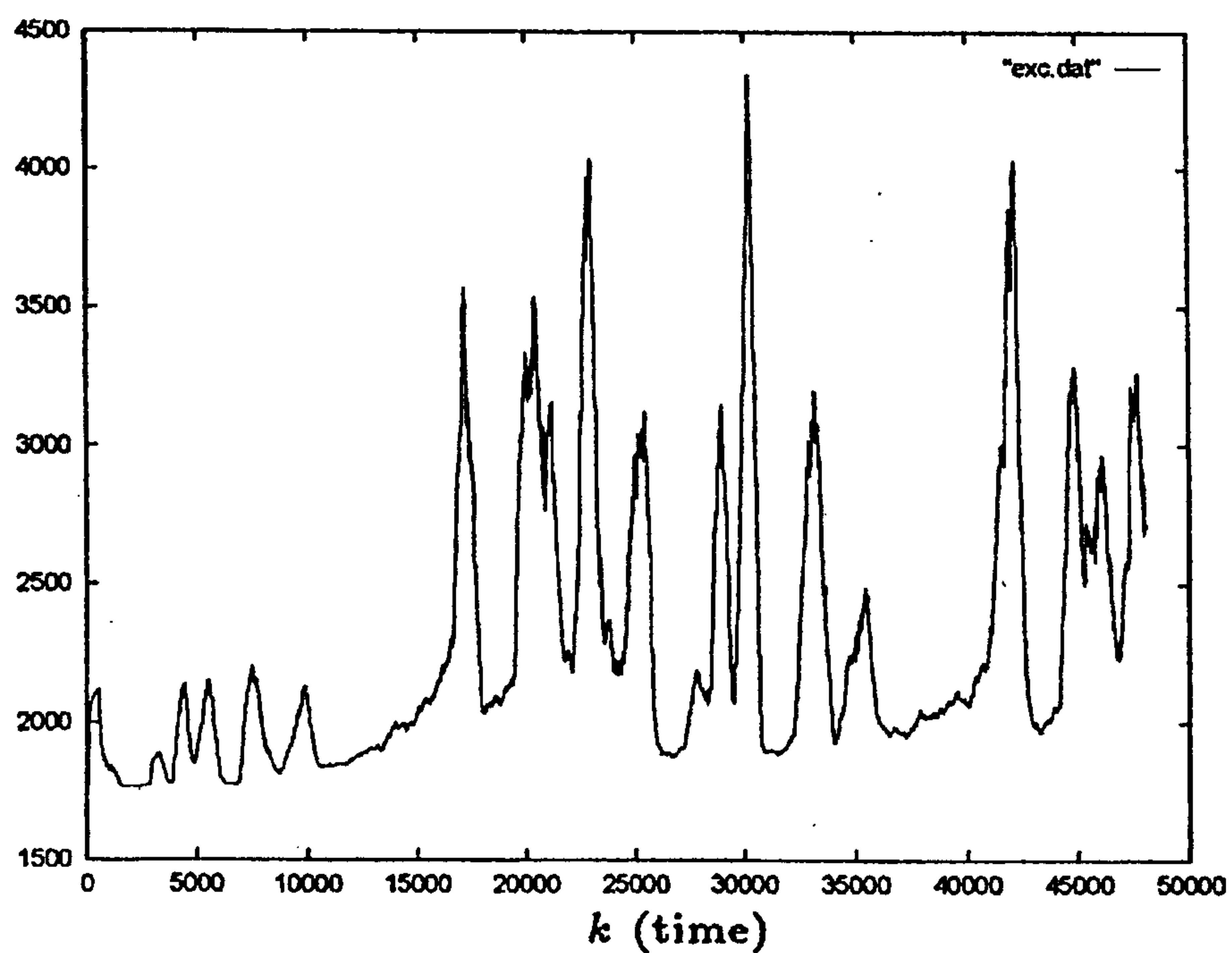
[図9]



[図10]



(a) 高速 H_∞ フィルタ

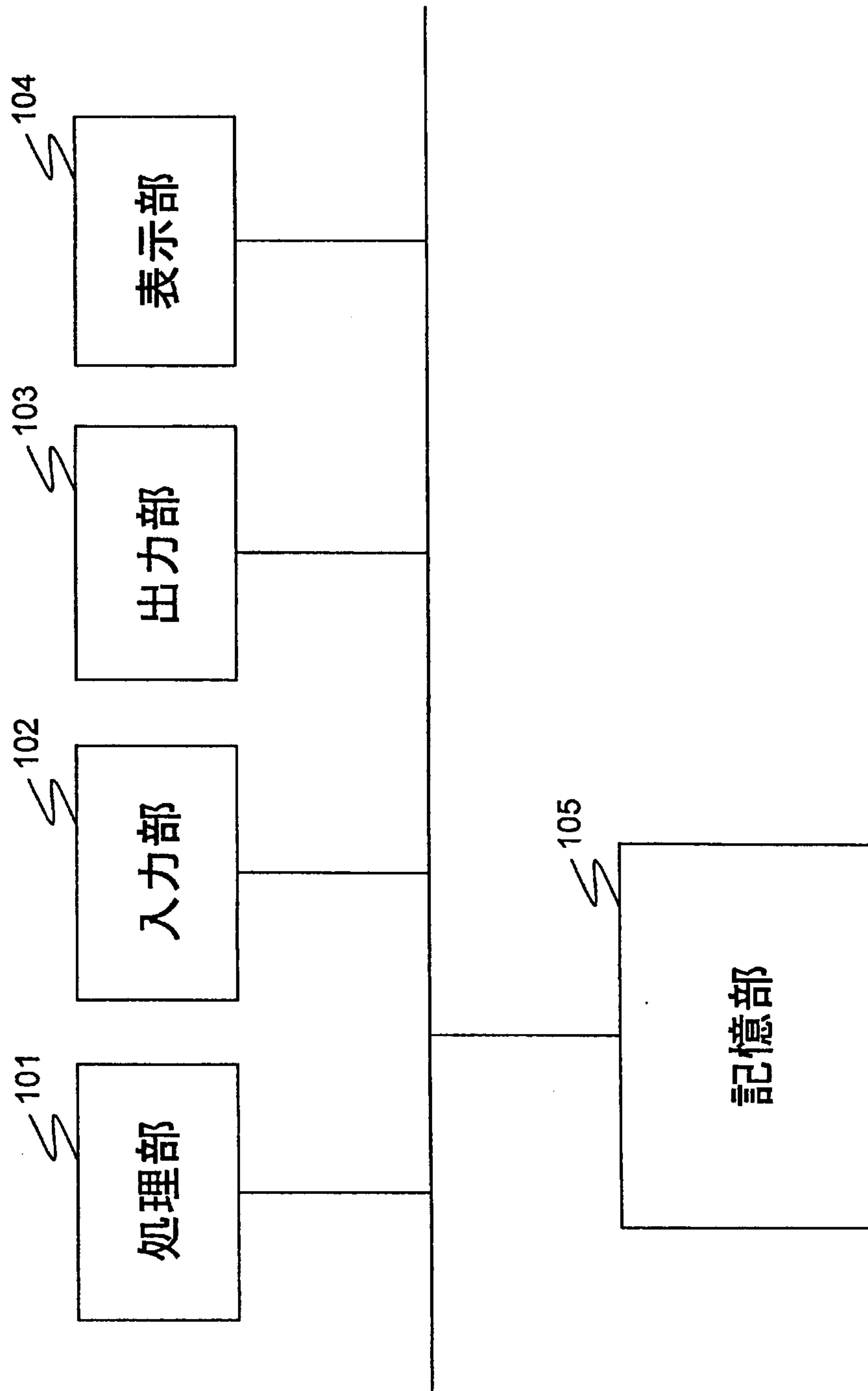


(b) 数値的安定化高速 H_∞ フィルタ

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[図11]

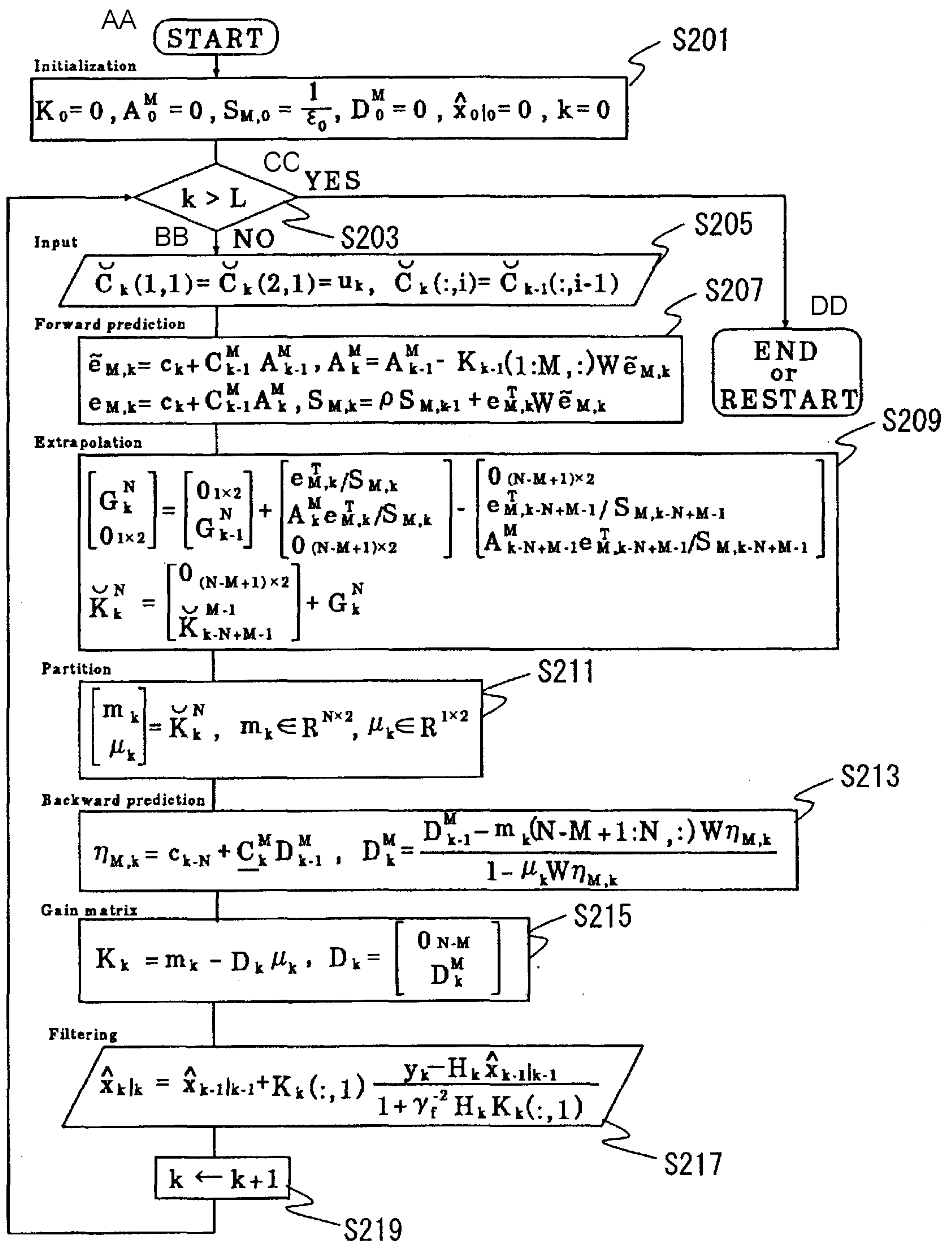


[図12]

	Mul.	Dev.
FHF	$26N + 13$	$2N + 3$
OR-FHF	$3N + 26M + 13$	$5M + 5$

[図13]

h_0	h_1	h_2	h_3	h_4	h_5
0.0	0.008	-0.012	0.064	0.013	-0.052
h_6	h_7	h_8	h_9	h_{10}	h_{11}
-0.007	0.039	0.011	0.0	-0.002	-0.009
h_{12}	h_{13}	h_{14}	h_{15}	h_{16}	h_{17}
-0.016	-0.013	-0.001	0.004	0.015	0.013
h_{18}	h_{19}	h_{20}	h_{21}	h_{22}	h_{23}
0.007	0.0	-0.001	-0.002	-0.001	0.0



$$\underline{C}_k^M = \check{C}_k(:, N - M + 1 : N), C_{k-1}^M = \check{C}_k(:, 2 : M + 1), H_k = \check{C}_k(1, 1 : N).$$

AA	DÉBUT
S201	INITIALISATION
S205	ENTRÉE
S207	PRÉDICTION DIRECTE
S209	EXTRAPOLATION
S211	DÉCOUPAGE
S213	PRÉDICTION RÉGRESSIVE
S215	MATRICE DE GAIN
S217	FILTRAGE
BB	NON
CC	OUI
DD	FIN OU REDÉMARRAGE