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M-transform and its Application to System Identification†

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A new method for signal transform by use of M-sequence, called M-transform, is proposed, and some properties of the M-transform are described. The essence of M-transform is to suppose any periodic time signal to be the output of a filter whose input is an M-sequence. The application of the M-transform to linear system identification is described, and the result of computer simulation show a good agreement with the theoretical consideration.

1. Introduction

In the field of instrument and control engineering , the extraction of useful information from a measured signal by use of signal processing such as stochastic data processing is very important and frequently used. In those cases, the method of signal processing depends on what kind of information we would like to extract from the measured signal. For example, if the information on the frequency characteristics is to be extracted, Fourier transform method would be used.

In the Fourier transform, sinusoidal functions are used as orthonormal functions for transform, and any time functions are transformed into frequency demain by considering any time functions are weighted sum of sinusoidal functions with various frequencies.

In this way, once we determine to use an orthonormal function, a signal transformation is achieved corresponding to the orthonormal function. Walsh transform or Hadamard transform are such examples.

This paper proposes a new method for signal transform, called M-transform, by making use of the fact that a pseudorandom M-sequence has a pseudo-orthogonal property;that is, the autocorrelation function of M-sequence is approximately equal to δ-function. The properties of M-transform are investigated and the application to linear system identification is described.

2. Definiton of M-transform

Let us consider an M-sequence $\{a_i\}(a_i = 0 \; or \; 1)$ of period $N(= 2^n - 1)$ which is generated by n-th order primitive polynomial $f(x)$ defined over Galios field $GF(2)$. And let $\{m_i\}(m_i = +1 or - 1)$ be the sequence obtained from the M-sequence by assigning 0 of a_i to $+1$ of m_i, and 1 of a_i to -1 of m_i.

Then the autocorrelation functoin $\phi_{mm}(k)$ is written as [9]

$$\phi_{mm}(k) = \frac{1}{N}\sum_{i=0}^{N-1} m_{i-k} m_i = \begin{cases} 1 & (\ k = 0, N, 2N, \cdots) \\ -\frac{1}{N} & (\ \text{otherwise}) \end{cases} \tag{1}$$

The period N is usually $10^2 \sim 10^4$, so $\frac{1}{N}$ becomes very small. Therefore Eqn.(1) is considered to represent that M-sequence $\{m_i\}$ and $\{m_{i+k}\}(k \neq 0, N, 2N, \cdots)$ are approximately orthogonal. So we call here that $\{m_i\}$ and $\{m_{i+k}\}$ are pseudo orthogonal.

Now let us construct a matrix $\boldsymbol{M}_i$ by use of m_i as follows.

$$\boldsymbol{M}_i = \begin{bmatrix} m_i & m_{i-1} & \dots & m_{i-N+1} \\ m_{i+1} & m_i & \dots & m_{i-N+2} \\ \vdots & \vdots & \ddots & \vdots \\ m_{i+N-1} & m_{i+N-2} & \dots & m_i \end{bmatrix} \tag{2}$$

When $\boldsymbol{M}_i^T$ denotes the transpose of $\boldsymbol{M}_i$, we have the following equation.

$$\boldsymbol{M}_i^T \boldsymbol{M}_i = \begin{bmatrix} N & -1 & \dots & -1 \\ -1 & N & \dots & -1 \\ \vdots & \vdots & \ddots & \vdots \\ -1 & -1 & \dots & N \end{bmatrix} \tag{3}$$

And the inverse of $\boldsymbol{M}_i^T \ \boldsymbol{M}_i$ becomes [9]

$$(\boldsymbol{M}_i^T \boldsymbol{M}_i)^{-1} = \frac{1}{N+1} \begin{bmatrix} 2 & 1 & \dots & 1 \\ 1 & 2 & \dots & 1 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 1 & \dots & 2 \end{bmatrix} \tag{4}$$

Now we consider a periodic time function $x(t)$ having its period $N\Delta t$, where Δt is the time increment. The sam-

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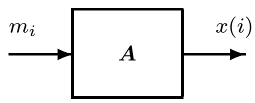

Fig. 1 Definition of M-transform

pled time function $x(i\Delta t)$ is denoted here as $x(i)$, for simplicity, where i is an integer considered as $modN$.

Then M-transform $\boldsymbol{A}$ of $x(i)$ is defined as

$$\boldsymbol{X}_i = \boldsymbol{M}_i \boldsymbol{A} \tag{5}$$

where

$$\begin{aligned} \boldsymbol{X}_i &= \{x(i), x(i+1), \cdots, x(i+N-1)\}^T \\ \boldsymbol{A} &= (\alpha_0, \alpha_1, \cdots, \alpha_{N-1})^T \end{aligned} \tag{6}$$

The M-transform $\boldsymbol{A}$ is determined uniquely by the following equation

$$\boldsymbol{A} = (\boldsymbol{M}_i^T \boldsymbol{M}_i)^{-1} \boldsymbol{M}_i^T \boldsymbol{X}_i \tag{7}$$

In other expression, we have

$$x(i) = \sum_{j=0}^{N-1} \alpha_j m_{i-j} \qquad (0 \le i \le N-1) \tag{8}$$

The meaning of M-transform $\boldsymbol{A}$ becomes as follows. From Eqn.(5), any periodic time function $\boldsymbol{X}_i$ is considered to be a weighted sum of M-sequences, with weighting coefficient $\boldsymbol{A}$. That is, any periodic time signal $x(i)$ is considered to be the output of a filter with impulse response $\{\alpha_i\}$, whose input is M-sequence $\{m_i\}$ as shown in **Fig. 1**. This corresponds to so-called *Pre-whitening* filter in case of white noise: any time function is considered to be the output of a filter whose input is white noise.

M-transfom $\boldsymbol{A}$ of $x(i)$ is called hereafter "M-$filter$" as shown in Fig.1.

M-transform resembles Fourier transform in the sense that, in M-transform, any periodic time signal is considered to be the weighted sum of pseudo-orthogonal M-sequence, whereas, in Fourier transform, any signal is considered to be the weighted sum of orthogonal sinusoidal functions.

3. Properties of M-transform

M-transform defined in Eqn.(5) has the following properties.

Property 1: Mean value

$$\frac{1}{N}\sum_{i=0}^{N-1} x(i) = -\frac{1}{N}\sum_{i=0}^{N-1} \alpha_i \tag{9}$$

Since each column of matrix $\boldsymbol{M}_i$ is one period M-sequence, the sum of elements of each column becomes -1. So Eqn.(9) holds. Namely, when the mean value of $x(i)$ is equal to zero, the mean of $\{\alpha_i\}$ is also zero.

Property 2: Autocorrelation function

The autocorrelation function $\phi_{xx}(k)$ of a signal $x(i)$ is obtained as follows.

$$\begin{aligned} \phi_{xx}(k) &= \frac{1}{N}\sum_{i=0}^{N-1} x(i-k)x(i) \\ &= \frac{1}{N}\boldsymbol{X}_{i-k}^T \boldsymbol{X}_i \\ &= \frac{1}{N}\boldsymbol{A}^T \boldsymbol{M}_{i-k}^T \boldsymbol{M}_i \boldsymbol{A} \end{aligned}$$

Here $\boldsymbol{M}_{i-k}^T$ $\boldsymbol{M}_i$ becomes

$$\boldsymbol{M}_{i-k}^T \boldsymbol{M}_i = \begin{array}{c} \begin{matrix} & & & k & & & \end{matrix} \\ \begin{bmatrix} -1 & -1 & \ldots & N & -1 & \ldots & -1 \\ -1 & -1 & \ldots & -1 & N & \ldots & -1 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ -1 & -1 & \ldots & -1 & -1 & \ldots & N \\ N & -1 & \ldots & -1 & -1 & \ldots & -1 \\ -1 & N & \ldots & -1 & -1 & \ldots & -1 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ -1 & -1 & \ldots & -1 & -1 & \ldots & -1 \end{bmatrix} \end{array}$$

Therefore, we have

$$\phi_{xx}(k) = \frac{N+1}{N}\sum_{i=0}^{N-1} \alpha_{i-k}\alpha_i - \frac{1}{N}(\sum_{i=0}^{N-1} \alpha_i)^2 \tag{10}$$

When the mean of $\{x(i)\}$ is zero, the mean of $\{\alpha_i\}$ is also zero due to property 1, so Eqn.(10) indicates that the autocorrelation function $\phi_{xx}(k)$ of $x(i)$ is caluculated by use of α_i in the same manner as in $\phi_{xx}(k)$, only the difference is the coefficient $N+1$.

Property 3: Crosscorrelation function

Let M-transform of signal $y(i)$ be $\boldsymbol{B}$.

$$\boldsymbol{Y}_i = \boldsymbol{M}_i \boldsymbol{B} \tag{11}$$

where

$$\begin{aligned} \boldsymbol{Y}_i &= \{y(i), y(i+1), \cdots, y(i+N-1)\}^T \\ \boldsymbol{B} &= (\beta_0, \beta_1, \cdots, \beta_{N-1})^T \end{aligned}$$

Then the crosscorrelation functoin $x(i)$ and $y(i)$ becomes

$$\begin{aligned} \phi_{xy}(k) &= \frac{1}{N}\sum_{i=0}^{N-1} x(i-k)y(i) \\ &= \frac{1}{N}\boldsymbol{X}_{i-k}^T \boldsymbol{Y}_i \end{aligned}$$

$$= \frac{1}{N} \boldsymbol{A}^T \boldsymbol{M}_{i-k}^T \boldsymbol{M}_i \boldsymbol{B}$$
$$= \frac{N+1}{N} \sum_{i=0}^{N-1} \alpha_{i-k}\beta_i$$
$$-\frac{1}{N}(\sum_{i=0}^{N-1} \alpha_i)(\sum_{i=0}^{N-1} \beta_i) \tag{12}$$

When the means of $x(i)$ and $y(i)$ are zero, the means of $\{\alpha_i\}$ and $\{\beta_i\}$ are also zero due to property 1. Therefore the crosscorrlation function $\phi_{xy}(k)$ is almost equal to $\phi_{\alpha_i\beta_i}(k)$ with only the difference of the coefficient $N+1$.

Property 4: Crosscorrelation function between an M-sequence and a signal $x(i)$

When a signal $x(i)$ is M-transformed to α_i via M-sequence as in Eqn.(5), the crosscorrelation function between the M-sequence $\{m_i\}$ and $\{x(i)\}$ becomes

$$\phi_{mx}(k) = \frac{1}{N} \sum_{i=0}^{N-1} m(i-k)x(i)$$
$$= \frac{1}{N} \sum_{i=0}^{N-1} m(i-k) \sum_{l=0}^{N-1} \alpha_l m_{i-l}$$
$$= \frac{1}{N} \sum_{l=0}^{N-1} \alpha_l \sum_{i=0}^{N-1} m(i-k)m(i-l)$$
$$= \sum_{l=0}^{N-1} \alpha_l \phi_{mm}(l-k)$$
$$= \frac{N+1}{N}\alpha_k - \frac{1}{N}\sum_{l=0}^{N-1}\alpha_l \tag{13}$$

That is, the crosscorrelation function between $\{m_i\}$ and $\{x_i\}$ can be described by α_i, and especially when the mean of $x(i)$ is zero, $\frac{N+1}{N}\alpha_k$ describes the crosscorrelation $\phi_{my}(k)$.

Property 5 : Input-output relation of linear system

Let $g(i)$ be the impulse response of a linear system whose input is $x(i)$. Then the output $y(i)$ is written as

$$y(i) = \sum_{j=0}^{N-1} g(j)x(i-j) \tag{14}$$

or

$$\boldsymbol{Y}_i = [\boldsymbol{X}_i, \boldsymbol{X}_{i-1}, \ldots, \boldsymbol{X}_{i-N+1}]\, \boldsymbol{G} \tag{15}$$

where

$$\boldsymbol{G} = (g(0), g(1), \cdots, g(N-1))^T \tag{16}$$

Then what is the relationship between M-tranform $\boldsymbol{B}$ of y and M-transform $\boldsymbol{A}$ of x ?

Submitting Eqn.(11) into Eqn.(15), we have

$$\boldsymbol{M}_i\boldsymbol{B} = [\boldsymbol{X}_i, \boldsymbol{X}_{i-1}, \ldots, \boldsymbol{X}_{i-N+1}]\, \boldsymbol{G} \tag{17}$$

Therefore

$$\boldsymbol{B} = (\boldsymbol{M}_i^T\boldsymbol{M}_i)^{-1} \cdot \left[\boldsymbol{M}_i^T\boldsymbol{X}_i, \boldsymbol{M}_i^T\boldsymbol{X}_{i-1}, \ldots, \boldsymbol{M}_i^T\boldsymbol{X}_{i-N+1}\right] \boldsymbol{G} \tag{18}$$

Here, $(\boldsymbol{M}_i^T\boldsymbol{M}_i)^{-1}$ is written in the next equation by using Eqn.(4).

$$(\boldsymbol{M}_i^T\boldsymbol{M}_i)^{-1} = \frac{1}{N+1} \times \left\{ \begin{bmatrix} 1 & 0 & \ldots & 0 \\ 0 & 1 & \ldots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \ldots & 1 \end{bmatrix} + \begin{bmatrix} 1 & 1 & \ldots & 1 \\ 1 & 1 & \ldots & 1 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 1 & \ldots & 1 \end{bmatrix} \right\} \tag{19}$$

or

$$\boldsymbol{M}_i^T\boldsymbol{X}_l = N \times \begin{bmatrix} \phi_{mx}(l-i) \\ \phi_{mx}(l-i+1) \\ \vdots \\ \phi_{mx}(l-i+N-1) \end{bmatrix} \tag{20}$$

where $(l = i,\ i-1,\ \ldots,\ i-N+1)$.

Submitting Eqn.(13) into $\phi_{mx}(\cdot)$ in Eqn.(20), the inside of [ ] in Eqn.(18) becomes

$$\left[\boldsymbol{M}_i^T\boldsymbol{X}_i, \boldsymbol{M}_i^T\boldsymbol{X}_{i-1}, \ldots, \boldsymbol{M}_i^T\boldsymbol{X}_{i-N+1}\right] = \left\{ (N+1) \begin{bmatrix} \alpha_0 & \alpha_{-1} & \ldots & \alpha_{-N+1} \\ \alpha_1 & \alpha_0 & \ldots & \alpha_{-N+2} \\ \vdots & \vdots & \ddots & \vdots \\ \alpha_{N-1} & \alpha_{N-2} & \ldots & \alpha_0 \end{bmatrix} - \begin{bmatrix} 1 & 1 & \ldots & 1 \\ 1 & 1 & \ldots & 1 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 1 & \ldots & 1 \end{bmatrix} \sum_{l=0}^{N-1}\alpha_l \right\} \tag{21}$$

When we submit Eqn.(19) and Eqn.(21) into Eqn.(18), we have

$$\beta_i = \sum_{j=0}^{N-1} g(j)\alpha_{i-j} \tag{22}$$

This means that the input-output relationship of a linear system between $x(i)$ and $y(i)$ in the time domain is exactly the same as that in the M-transformed domain.

In addition, the crosscorrelation function between the input $x(i)$ and the output $y(i)$ is known as

$$\phi_{xy}(k) = \sum_{j=0}^{N-1} g(j)\phi_{xx}(k-j) \tag{23}$$

Submitting Eqn.(10) and Eqn.(12) into Eqn.(23), we have

$$\frac{N+1}{N}\sum_{i=0}^{N-1}\alpha_{i-k}\beta_i - \frac{1}{N}(\sum_{i=0}^{N-1}\alpha_i)(\sum_{i=0}^{N-1}\beta_i)$$
$$= \sum_{j=0}^{N-1} g(j) \left\{ \frac{N+1}{N}\sum_{i=0}^{N-1}\alpha_{i-k+j}\alpha_i - \frac{1}{N}(\sum_{i=0}^{N-1}\alpha_i)^2 \right\}$$

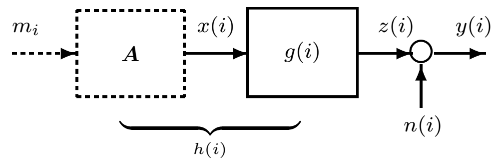

Fig. 2 Application to Linear System identification

$$= \frac{N+1}{N} \sum_{j=0}^{N-1} g(j) \sum_{i=0}^{N-1} \alpha_{i-k+j}\alpha_i - \frac{1}{N} \sum_{j=0}^{N-1} g(j) \left(\sum_{i=0}^{N-1} \alpha_i \right)^2 \tag{24}$$

From Eqn.(22), the summation of β_i over its period is written as

$$\sum_{i=0}^{N-1} \beta_i = \sum_{j=0}^{N-1} g(j) \sum_{i=0}^{N-1} \alpha_{i-j}$$

Therefore, the second term of lefthand side of Eqn.(24) is equal to the second term of righthand side of Eqn.(24). Thus we have

$$\frac{1}{N} \sum_{i=0}^{N-1} \alpha_{i-k}\beta_i = \sum_{j=0}^{N-1} g(j) \frac{1}{N} \sum_{i=0}^{N-1} \alpha_{i-k+j}\alpha_i$$

$$\therefore \quad \phi_{\alpha\beta}(k) = \sum_{j=0}^{N-1} g(j)\phi_{\alpha\alpha}(k-j) \tag{25}$$

which has the same form as in Eqn.(23).

4. Application to Linear System Identification

4.1 Principle

Let us consider the identification of a linear system having the impulse response of $g(i)$ whose input is $x(i)$ and output is $z(i)$ as shown in **Fig. 2**. Let us also assume that an independent noise $n(i)$ is added to the output $z(i)$ and $y(i) = z(i) + n(i)$ is observed.

Among many identification methods for linear system, M-sequence correlation method [1)~3)] is known as one of the most simple methods for identification, since all we have to do is to multiply a matrix with the crosscorrelation function between the input M-sequence and its output. It has two advantages; (1) Calculation is easily carried out since the input M-sequence is of two-valued signal, so the multiplication is carried out by addition or substraction. (2) Because M-sequence is a periodic deterministic signal, the crosscorrelation function is determined in a period and there are no statistical dispersion due to finite averaging time. M-sequence correlation method is a very simple, useful method, but in order to use this method, M-sequence must be applied to the input to the system. When we would like to identify a system under normal operating condition such as in case of chemical process, we sometimes encounter the case where it is difficult to apply a special signal for identification to the operating system. In those cases, the identification must be carried out by use of only input $x(i)$ and output $y(i)$.

In this section, the authors show that the input $x(i)$ is considered to be the output of a filter (M-filter $\boldsymbol{A}$) whose input is M-sequence $\{m_i\}$, so when the cascaded system of $\boldsymbol{A}$ and $g(i)$ is considered to be a linear system whose impulse response is $h(i)$, the input to $h(i)$ is an M-sequence and the output of $h(i)$ is $y(t)$. Therefore we can apply M-sequence correlation method to this system for obtaining $h(i)$ and then $g(i)$, since $\boldsymbol{A}$ is already known.

Firstly M-transform $\boldsymbol{A}$ of $x(i)$ is obtained from Eqn.(7). And then,

$$y(i) = \sum_{j=0}^{N-1} h(j)m_{i-j} + n(i) \tag{26}$$

Therefore

$$\boldsymbol{Y}_i = \boldsymbol{M}_i\boldsymbol{H} + \boldsymbol{N_i} \tag{27}$$

where

$$\boldsymbol{Y}_i = (y(i), y(i+1), \cdots, y(i+N-1))^T \tag{28}$$

$$\boldsymbol{H} = (h(0), h(1), \cdots, h(N-1))^T \tag{29}$$

$$\boldsymbol{N_i} = (n(i), n(i+1), \cdots, n(i+N-1))^T \tag{30}$$

So by use of M-sequence correlation method [9)], we have

$$\boldsymbol{H} = (\boldsymbol{M}_i^T\boldsymbol{M}_i)^{-1}\boldsymbol{M}_i^T\boldsymbol{Y}_i \tag{31}$$

Since $h(i)$ is an impulse response of the cascaded system of M-filter $\boldsymbol{A}$ and linear system $g(i)$,

$$h(i) = \sum_{j=0}^{N-1} \alpha(i-j)g(j) \tag{32}$$

So we have

$$\boldsymbol{H} = \boldsymbol{\alpha}\boldsymbol{g} \tag{33}$$

where

$$\boldsymbol{g} = (g(0), g(1), \cdots, g(N-1))^T \tag{34}$$

$$\boldsymbol{\alpha} = \begin{bmatrix} \alpha_0 & \alpha_{-1} & \cdots & \alpha_{-N+1} \\ \alpha_1 & \alpha_0 & \cdots & \alpha_{-N+2} \\ \vdots & \vdots & \ddots & \vdots \\ \alpha_{N-1} & \alpha_{N-2} & \cdots & \alpha_0 \end{bmatrix} \tag{35}$$

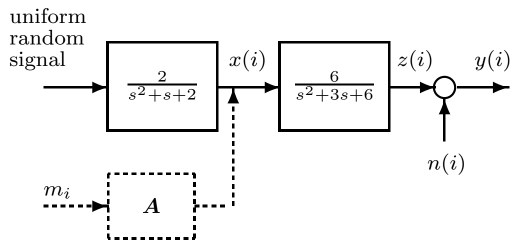

Fig. 3 Identification of linear system by use of M-transform

Therefore, the impulse response $g(i)$ is obtained as follows,

$$\boldsymbol{g} = \boldsymbol{\alpha}^{-1}\boldsymbol{H} \tag{36}$$

4. 2 Simulation

In order to verify the usefulness of the above mentioned method, a simulation is carried out for the system shown in **Fig. 3**. A uniform random signal is applied to a second-order system, and let the output be $x(i)$ as shown in **Fig. 4**. $x(i)$ becomes the input to the linear system to be identified. The output $z(i)$ is added by a noise $n(i)$ to be the system output $y(i)$, as shown in **Fig. 5** (Here SN ratio is about $30dB$). The input $x(i)$ is now considered to be the output of an M-filter $\boldsymbol{A}$ whose input is an M-sequence. $\boldsymbol{A}$ is obtained by use of Eqn.(7) and is shown in **Fig. 6**. Here the M-sequence $\{m_i\}$ used is of 7 degree having a characteristic polynomial $f(x) = 375$ in octal notation. Now from M-sequence correlation method, we can obtain the impulse response $h(i)$ between the input $\{m_i\}$ and output $\{y_i\}$ by using Eqn.(31), as is shown in **Fig. 7**. Lastly from Eqn.(36) we have the impulse response $g(i)$ as is shown in **Fig. 8**. Here a lag window having the effect of ensemble average is used for originally obtained $g(i)$. In Fig. 8, the solid line shows the theoretical impluse response, and "$\circ$" denote the obtained $g(i)$, showing a good agreement between them although there are a little dispersions due to the effect of noise.

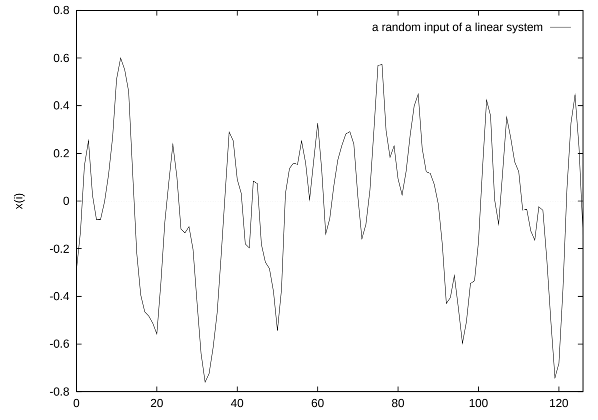

Fig. 4 Input signal of the system to be identified

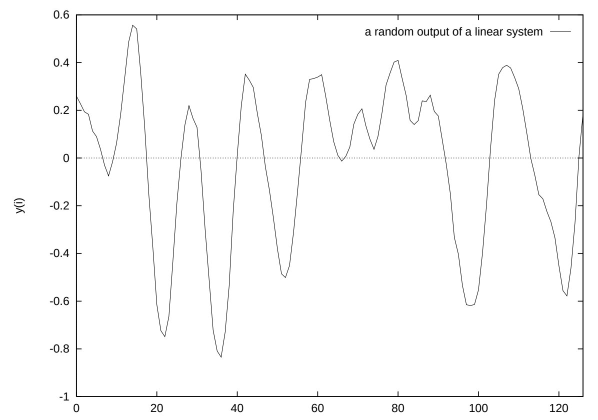

Fig. 5 Output signal of the system

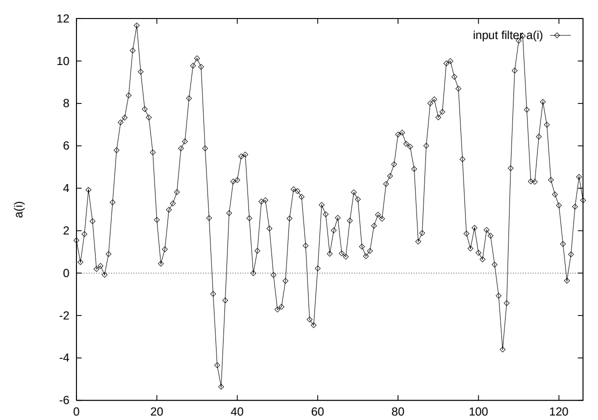

Fig. 6 M transform of x(i)

5. Conclusion

A new method of signal transformation(called M-transform) by use of pseudo-orthogonal property of M-sequence is proposed, and several properties of M-transform are described with application to linear system identification. The main characteristics of M-transform is that any periodic time signal is considered to be the output of a filter (called M-filter) whose input is an M-sequence. This property resembles the so called prewhitening in which any time signal is considered to be the output of a filter whose input is white noise.

This M-transform is applied to the identification of linear system in which the input and output are observed and the impulse response of the system is to be obtained. The result of simulation shows that this method of system idetification becomes a new method for linear system identification using so-callled M-sequence correlation method.

Other applications of M-transform are under development.

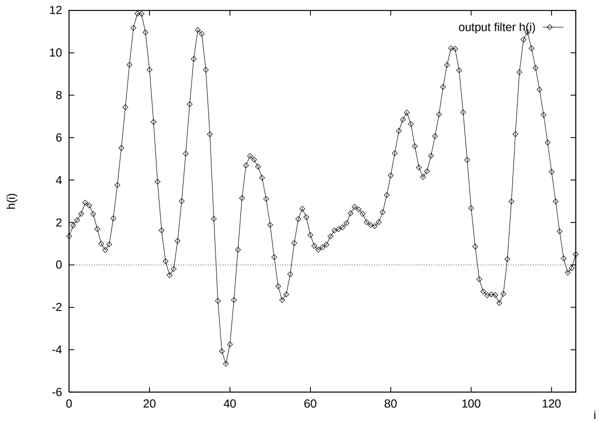

Fig. 7 Obtained h(i)

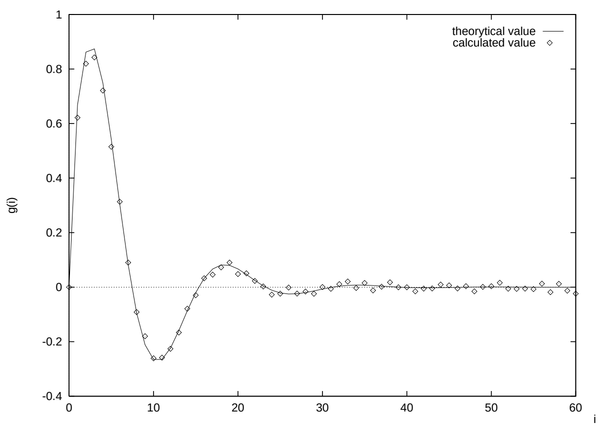

Fig. 8 Comparison of the obtained g(i) with theoretical one

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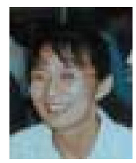

She graduated from Department of Computer at Xi An Science and Technology University, China in 1985. After she got ME degree from the same university, she became a research assistant at Department of Electric Engineering, Xi An Mining Institute, China in 1988. Then she became a teacher in the same institute in 1991. She entered Graduate School of Science and Technology, Kumamoto University,Japan, in 1996. In 1999, she got PhD degree from Kumamoto University. Her research interest includes identification of control systems by use of M-sequence.

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