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SIGNAL PROCESSING FOR NOISE CANCELLATION IN ACTUAL ELECTROMAGNETIC ENVIRONMENT

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Abstract—The observed phenomena in actual electromagnetic environment are inevitably contaminated by the background noise of arbitrary distribution type. Therefore, in order to evaluate the electromagnetic environment, it is necessary to establish some signal processing methods to remove the undesirable effects of the background noise. In this paper, we propose a noise cancellation method for estimating a specific signal with the existence of background noise of non-Gaussian distribution. By applying the well-known least mean squared method for the moment statistics with several orders, a practical method for estimating the specific signal is derived. The effectiveness of the proposed theoretical method is experimentally confirmed by applying it to an estimation problem in actual magnetic field environment.

1. INTRODUCTION

The specific signal in the actual electromagnetic wave frequently shows some very complex fluctuation forms of non-Gaussian type owing to natural, social and human factors [1–3]. Furthermore, the observed data are inevitably contaminated by the background noise of arbitrary distribution type [4, 5]. In these situations, it is often desirable to estimate several evaluation quantities such as the peak value, the amplitude probability distribution, the average crossing rate, the pulse spacing and duration distributions, etc. of the specific signal. Without

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losing their mutual relationships, it is indispensable to estimate the original wave fluctuation form itself of the specific signal based on the observed noise data.

In this study, a signal processing method for estimating a specific signal with the existence of background noise of non-Gaussian distribution forms is proposed. More specifically, by paying attention to the power state variable for a specific signal in the electromagnetic environment, which exhibits complex probability distribution forms, we propose a new type of signal processing method for estimating a specific signal. In the case of considering the power state variable, a physical mechanism of contamination by a background noise can be reflected in the state estimation method by using an additive property between the specific signal and background noise. The proposed method positively utilizes the additive property of power state variables in the derivation processes of the estimation algorithm.

The effectiveness of the proposed theoretical method is experimentally confirmed by applying it to the actual estimation problem in specific magnetic field environment.

2. BACKGROUND

Hitherto many methodological studies have been reported on the state estimation for stochastic systems [6–8]. However, many standard estimation methods proposed previously in a study of stochastic systems are restricted only to the Gaussian distribution [9, 10]. Several state estimation methods for nonlinear system have been also proposed by assuming the Gaussian distribution of system and observation noises [11–15]. The actual electromagnetic environment often shows an intricate fluctuation pattern rather than the standard Gaussian distribution. In our previous studies [16–18], several state estimation methods for a stochastic environment system with non-Gaussian fluctuations have been proposed on the basis of expansion expressions for the probability distribution. Furthermore, state estimation methods for stochastic systems with complex characteristics and/or unknown structure have been proposed by using Bayes theorem on probability distribution [19–21]. Since the above previously reported estimation algorithms are based on the whole of the probability distribution, their derivation processes became rather complicated. Especially, though the unscented Kalman filter (UKF) and particle filter are useful for non-linear systems, UKF considers only the mean and variance of variables, and the particle filter needs very complicated algorithm based on Monte carlo simulation [15, 21].

In this study, instead of focusing on the whole of the probability distribution in the previous studies [16–18, 21], by applying the well-known least mean squared method [22] for the moment statistics with several orders, a simplified estimation algorithm is derived from the practical viewpoint.

3. A NOISE CANCELLATION METHOD FOR ELECTROMAGNETIC ENVIRONMENT

Let us consider the electromagnetic environment with the power state variable fluctuating in a non-stationary form, and express the system equation as:

$$x_{k+1} = Fx_k + Gu_k, \tag{1}$$

where x_k is the unknown specific signal at a discrete time k, to be estimated. The statistics of the random input u_k and two parameters F and G can be estimated by the auto-correlation technique [16]. On the other hand, based on the additive property of power state variables, the observation y_k contaminated by the background noise v_k can be expressed as:

$$y_k = x_k + v_k. \tag{2}$$

In order to derive an estimation algorithm for a specific signal based on the noisy observation, we positively pre-establish the estimates on the power function of x_k, as follows:

$$\begin{aligned} \hat{x}_k &= a_{10} + a_{11}H_1\left(\frac{y_k - y_k^*}{\sqrt{\Omega_k}}\right), \\ \hat{x}_k^2 &= a_{20} + a_{21}H_1\left(\frac{y_k - y_k^*}{\sqrt{\Omega_k}}\right) + a_{22}H_2\left(\frac{y_k - y_k^*}{\sqrt{\Omega_k}}\right), \\ \hat{x}_k^3 &= a_{30} + a_{31}H_1\left(\frac{y_k - y_k^*}{\sqrt{\Omega_k}}\right) + a_{32}H_2\left(\frac{y_k - y_k^*}{\sqrt{\Omega_k}}\right) \\ &\quad + a_{33}H_3\left(\frac{y_k - y_k^*}{\sqrt{\Omega_k}}\right), \\ &\quad \ldots, \end{aligned} \tag{3}$$

where $H_n(\ )$ is Hermite polynomial with nth orders [23, 24], and a_{ij} denote the regression coefficients. Considering (2), two parameters $y_k^*(\equiv < y_k|Y_{k-1} >$; expectation on y_k conditioned by $Y_{k-1})$ and $\Omega_k(\equiv < (y_k - y_k^*)^2|Y_{k-1} >$; expectation on $(y_k - y_k^*)^2$ conditioned by $Y_{k-1})$ can be given by

$$\begin{aligned} &y_k^* = x_k^* + \bar{v}_k,\ \ \Omega_k = \Gamma_k + R_k, \\ &(\bar{v}_k = < v_k >,\ \ R_k = < (v_k - \bar{v}_k)^2 >) \end{aligned} \tag{4}$$

with

$$x_k^* \equiv < x_k|Y_{k-1} >, \ \Gamma_k \equiv < (x_k - x_k^*)^2|Y_{k-1} >, \tag{5}$$

where $Y_{k-1}(\equiv \{y_1, y_2, \ldots, y_{k-1}\})$ is a set of observation data up to $k-1$, and $<>$ denotes an averaging operation with respect to the random variables.

Next, by applying the well-known least mean squared method for the moment statistics with several orders, a practical estimation method is derived. More specifically, the regression coefficients in (3) are decided so as to minimize the criteria:

$$\begin{aligned} J_1 &= < (x_k - \hat{x}_k)^2 \left| Y_{k-1} > \rightarrow Minimize, \right. \\ J_2 &= < \left(x_k^2 - \hat{x}_k^2\right)^2 \left| Y_{K-1} > \rightarrow Minimize, \right. \\ J_3 &= < \left(x_k^3 - \hat{x}_k^3\right)^2 \left| Y_{k-1} > \rightarrow Minimize, \right. \\ & \quad \ldots . \end{aligned} \tag{6}$$

After substituting (3) in (6) and differentiating it with respect to each regression coefficient, and then using the statistical property of Hermite polynomial, the following relationships are derived.

From $\partial J_1/\partial a_{10} = \partial J_1/\partial a_{11} = \partial J_2/\partial a_{20} = \partial J_2/\partial a_{21} = \partial J_2/\partial a_{22} = 0$, we obtain

$$a_{10} = x_k^*, \ a_{11} = \frac{\Gamma_k}{\sqrt{\Omega_k}}, \ a_{20} = \Gamma_k + x_k^{*2}, \tag{7}$$

$$\begin{aligned} & a_{21} + < H_3\left(\frac{y_k - y_k^*}{\sqrt{\Omega_k}}\right) \Big| Y_{k-1} > a_{22} \\ & = \frac{1}{\sqrt{\Omega_k}} \left\{ \left(\sqrt{\Gamma_k}\right)^3 < H_3\left(\frac{x_k - x_k^*}{\sqrt{\Gamma_k}}\right) \Big| Y_{k-1} > +2\Gamma_k x_k^* \right\}, \end{aligned} \tag{8}$$

$$\begin{aligned} & < H_3\left(\frac{y_k - y_k^*}{\sqrt{\Omega_k}}\right) \Big| Y_{k-1} > a_{21} + 2a_{22} \\ & = \frac{2}{\Omega_k} \left\{ \Gamma_k^2 + \left(\sqrt{\Gamma_k}\right)^3 < H_3\left(\frac{x_k - x_k^*}{\sqrt{\Gamma_k}}\right) \Big| Y_{k-1} > x_k^* \right\}, \end{aligned} \tag{9}$$

where the following relationships have to be considered in (8) and (9).

$$\begin{aligned} & < H_3\left(\frac{y_k - y_k^*}{\sqrt{\Omega_k}}\right) \Big| Y_{k-1} > = \frac{1}{\left(\sqrt{\Omega_k}\right)^3} \left\{ \left(\sqrt{\Gamma_k}\right)^3 < H_3\left(\frac{x_k - x_k^*}{\sqrt{\Gamma_k}}\right) \Big| Y_{k-1} > \right. \\ & \left. + \left(\sqrt{R_k}\right)^3 < H_3\left(\frac{v_k - \bar{v}_k}{\sqrt{R_k}}\right) > \right\}. \end{aligned} \tag{10}$$

By solving the simultaneous equations of (8) and (9), the regression coefficients a_{21} and a_{22} are obtained.

Furthermore, from $\partial J_3/\partial a_{30} = \partial J_3/\partial a_{31} = \partial J_3/\partial a_{32} = \partial J_3/\partial a_{33} = 0$, we obtain

$$\begin{aligned}
&a_{30}+ < H_3\left(\frac{y_k - y_k^*}{\sqrt{\Omega_k}}\right)\Big|Y_{k-1} > a_{33} \\
&= \left(\sqrt{\Gamma_k}\right)^3 < H_3\left(\frac{x_k - x_k^*}{\sqrt{\Gamma_k}}\right)\Big|Y_{k-1} > +3x_k^*\Gamma_k + x_k^{*3}, \qquad (11) \\
&a_{31}+ < H_3\left(\frac{y_k - y_k^*}{\sqrt{\Omega_k}}\right)\Big|Y_{k-1} > a_{32} \\
&= \frac{3}{\sqrt{\Omega_k}}\left\{\Gamma_k^2 + x_k^*\left(\sqrt{\Gamma_k}\right)^3 < H_3\left(\frac{x_k - x_k^*}{\sqrt{\Gamma_k}}\right)\Big|Y_{k-1} > +x_k^{*2}\Gamma_k\right\}, \qquad (12) \\
&< H_3\left(\frac{y_k - y_k^*}{\sqrt{\Omega_k}}\right)\Big|Y_{k-1} > a_{31} + 2a_{32} + 6 < H_3\left(\frac{y_k - y_k^*}{\sqrt{\Omega_k}}\right)\Big|Y_{k-1} > a_{33} \\
&= \frac{2}{\Omega_k}\left\{5\left(\sqrt{\Gamma_k}\right)^5 + \frac{3}{2}x_k^{*2}\left(\sqrt{\Gamma_k}\right)^3 - \frac{\left(\sqrt{\Gamma_k}\right)^5}{2}\right\} \\
&< H_3\left(\frac{x_k - x_k^*}{\sqrt{\Gamma_k}}\right)\Big|Y_{k-1} > +3x_k^*\Gamma_k^2, \qquad (13) \\
&< H_3\left(\frac{y_k - y_k^*}{\sqrt{\Omega_k}}\right)\Big|Y_{k-1} > a_{30} + 6 < H_3\left(\frac{y_k - y_k^*}{\sqrt{\Omega_k}}\right)\Big|Y_{k-1} > a_{32} + 66a_{33} \\
&= \frac{1}{\left(\sqrt{\Omega_k}\right)^3}\left\{21x_k^*\Gamma_k + x_k^{*3}\left(\sqrt{R_k}\right)^3 < H_3\left(\frac{v_k - \bar{v}_k}{\sqrt{R_k}}\right) >\right\} \\
&+ \left(\sqrt{\Gamma_k}\right)^3 < H_3\left(\frac{x_k - x_k^*}{\sqrt{\Gamma_k}}\right)\Big|Y_{k-1} > +66\Gamma_k^3 + \big(3x_k^*\Gamma_k^3 \\
&+ x_k^{*3}\big)\left(\sqrt{R_k}\right)^3 < H_3\left(\frac{v_k - \bar{v}_k}{\sqrt{R_k}}\right) > . \qquad (14)
\end{aligned}$$

In the derivation of (11)–(14), the assumption is made in practice that the only third order statistics $< H_3(\ )|Y_{k-1} >$ of the Hermite polynomial is considered as non-Gaussian property and the higher order statistics above the fourth order are zero for the specific signal used: $< H_n(\ )|Y_{k-1} >= 0$ $(n = 4, 5, \ldots)$.

If assuming the Gaussian distribution of the fluctuation after considering the estimates up to second order statistics in (3), the following relationships are obtained.

$$\hat{x}_k = x_k^* + \frac{\Gamma_k}{\Omega_k}\left(y_k - y_k^*\right), \qquad (15)$$

$$\hat{x}_k^2 = \Gamma_k + x_k^{*2} - \frac{\Gamma_k^2}{\Omega_k} + 2x_k^*\frac{\Gamma_k}{\Omega_k}(y_k - y_k^*) + \frac{\Gamma_k^2}{\Omega_k^2}(y_k - y_k^*)^2. \qquad (16)$$

Thus, the variance of estimation error defined by $P_k = \hat{x}_k^2 - \hat{x}^2$ can be expressed as

$$P_k = \Gamma_k - \frac{\Gamma_k^2}{\Gamma_k + R_k}. \tag{17}$$

Estimates (15) and (17) coincide with the algorithm of Kalman filter [9, 10]. Therefore, it is obvious the proposed estimation method includes the Kalman filter as a special case.

Finally, by considering (1), the prediction algorithm essential for performing the recursive estimation can be expressed as

$$x_{k+1}^* = F\hat{x}_k + G\bar{u}_k, \ (\bar{u}_k =< u_k >), \tag{18}$$

$$\Gamma_{k+1} = F^2 P_k + G^2 Q_k, \ \left(Q_k =< (u_k - \bar{u}_k)^2 >\right), \tag{19}$$

$$\begin{aligned} &< H_3 \left(\frac{x_{k+1} - x_{k+1}^*}{\sqrt{\Gamma_{k+1}}} \right) \Big| Y_k > \\ &= \frac{1}{(\Gamma_{k+1})^3} \left\{ F^3 < H_3 \left(\frac{x_k - \hat{x}_k}{\sqrt{P_k}} \right) \Big| Y_k > (\sqrt{P_k})^3 \right. \\ &\left. + G^3 < H_3 \left(\frac{u_k - \bar{u}_k}{\sqrt{Q_k}} \right) > \left(\sqrt{Q_k} \right)^3 \right. \end{aligned} \tag{20}$$

with

$$P_k = \hat{x}_k^2 - \hat{x}_k^2, \tag{21}$$

$$< H_3 \left(\frac{x_k - \hat{x}_k}{\sqrt{P_k}} \right) \Big| Y_k >= \frac{1}{\left(\sqrt{P_k}\right)^3} \left(\hat{x}_k^3 - 3\hat{x}_k^2 \hat{x}_k + 2\hat{x}_k^3 \right). \tag{22}$$

Therefore, by combining the estimation algorithm of (3) and reflecting the predictions involving the regression coefficients, which are functions of x_k^*, Γ_k, $< H_3((x_k - x_k^*)/\sqrt{\Gamma_k})|Y_{k-1} >$ with the prediction algorithms of (18)–(22) which are given by the functions of $\hat{x}_k$, $\hat{x}_k^2$, $\hat{x}_k^3$, the recurrence estimation of the specific signal can be achieved.

4. EXPERIMENT

By adopting a personal computer in the actual working environment as specific information equipment, the proposed method is applied to estimate the magnetic field leaked from a VDT (Video Display Terminal) under the situation of playing a computer game. Some studies on the fluctuation of electromagnetic wave leaked from electronic equipment in the actual working environment have become important recently because of the increased use of various information and communication systems like the personal computer and portable radio transmitters, especially concerning the individual and compound effects on a living body. It is well-known that there are too many unsolved questions on VDT symptom groups to study, such as the complaint of general malaise, the effect on a pineal body, an allergic or stress reaction, any relationship to cataract formation or leulemia and so on (for example, see references [25, 26]. In these investigations, one of the first important problems generally pointed out is to find any quantitative evaluation method. The proposed method in this paper is a fundamental study to evaluate quantitatively the specific signal on electromagnetic wave.

More specifically, in the actual office environment of using two computers, the magnetic field strength leaked from a specific computer is estimated by regarding the magnetic field from the other computer as background noise. The data of magnetic field strength of the specific signal and the background noise were measured respectively by use of a HI-3603 type electromagnetic field survey meter. By use of the additive property of the power state variables, the observation data were obtained. Since the specific magnetic field shows approximately a constant, the system equation with $F = 1$, $G = 0$ in (1) is introduced. Furthermore, by use of the additive property of power state variables, the observation equation is expressed as (2). The estimated results in two cases of assuming a Gaussian property and considering the non-Gaussian property in the proposed estimation algorithm are shown in Figs. 1 and 2, respectively. The both results of estimation show good agreement with the true values in spite of artificially employing three types of arbitrary initial values. Furthermore, the estimated process by considering the non-Gaussian property converges more rapidly to the true values, as compared with the case of assuming the Gaussian property. In Fig. 2, the "Estimated results" consider the estimation algorithm in (3) with the higher order statistics of the third order in addition to the usual first and second orders. The statistics of the third order of background noise are reflected in the coefficients a_{21}, a_{22}, a_{30}, a_{31}, a_{32} and a_{33} in the estimation algorithm as the non-Gaussian property. By considering the non-Gaussian property in the estimation algorithm, accurate estimation results are obtained. It is expected that more accurate estimates can be obtained by considering the statistics above the fourth order as non-Gaussian property from the theoretical viewpoint. Furtermore, a computer simulation is performed in order to compare the proposed method considering non-Gaussian property with the case assuming the Gaussian property (cf. Appendix A).

Next, because the statistics of the background noise in (2) are often unknown, the following noise model is introduced.

$$v_k = \alpha_k e_k + \beta_k, \tag{23}$$

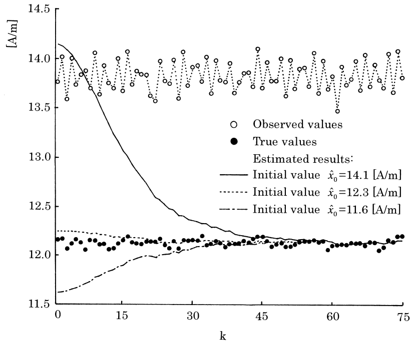

Figure 1. Estimation results by assuming Gaussian property.

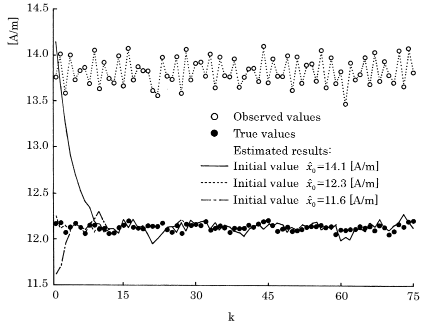

Figure 2. Estimation results by considering non-Gaussian property.

where α_k and β_k are unknown parameters, and e_k denotes a random noise with mean 0 and variance 1. For the simultaneous estimation of the parameters α_k and β_k with the specific signal x_k, by introducing a simple dynamical model:

$$\alpha_{k+1} = \alpha_k, \ \beta_{k+1} = \beta_k, \tag{24}$$

the estimates for the parameters have to be considered in a simultaneous form with the estimates of x_k. (For the simplification of the estimation algorithm, only the power functions with first and second orders are considered):

$$\begin{aligned}
\hat{x}_k &= b_{10} + b_{11} L_1^{(m_k^*-1)}\left(\frac{y_k}{s_k^*}\right),\\
\hat{x}_k^2 &= b_{20} + b_{21} L_1^{(m_k^*-1)}\left(\frac{y_k}{s_k^*}\right) + b_{22} L_2^{(m_k^*-1)}\left(\frac{y_k}{s_k^*}\right),\\
\hat{\alpha}_k &= c_{10} + c_{11} L_1^{(m_k^*-1)}\left(\frac{y_k}{s_k^*}\right),\\
\hat{\alpha}_k^2 &= c_{20} + c_{21} L_1^{(m_k^*-1)}\left(\frac{y_k}{s_k^*}\right) + c_{22} L_2^{(m_k^*-1)}\left(\frac{y_k}{s_k^*}\right),\\
\hat{\beta}_k &= d_{10} + d_{11} L_1^{(m_k^*-1)}\left(\frac{y_k}{s_k^*}\right),\\
\hat{\beta}_k^2 &= d_{20} + d_{21} L_1^{(m_k^*-1)}\left(\frac{y_k}{s_k^*}\right) + d_{22} L_2^{(m_k^*-1)}\left(\frac{y_k}{s_k^*}\right),
\end{aligned} \tag{25}$$

where $L_n^{(m-1)}(\ )$ in a Laguerre polynomial of n-th order [23, 24], and

$\hat{\alpha}_k$, $\hat{\alpha}_k^2$, $\hat{\beta}_k$, $\hat{\beta}_k^2$ denote the estimates of α_k, α_k^2, β_k, β_k^2, respectively. The Laguerre polynomial connected with the Gamma distribution is suitable for variables defined within only a positive range such as the electromagnetic signal in a power scale [23, 24]. Furthermore, b_{ij}, c_{ij} and d_{ij} denote the regression coefficients expressing in Appendix B. Considering (2) and (23), two parameters m_k^* and s_k^* can be given by

$$m_k^* \equiv \frac{(y_k^*)^2}{\Omega_k}, \ s_k^* \equiv \frac{\Omega_k}{y_k^*},$$
$$y_k^* = x_k^* + \beta_k^*, \ \Omega_k = \Gamma_k + \Gamma_{\alpha_k} + \Gamma_{\beta_k} + (\alpha_k^*)^2 \tag{26}$$

with

$$\alpha_k^* \equiv < \alpha_k | Y_{k-1} >, \ \Gamma_{\alpha_k} \equiv < (\alpha_k - \alpha_k^*)^2 \left| Y_{k-1} \right. >,$$
$$\beta_k^* \equiv < \beta_k | Y_{k-1} >, \ \Gamma_{\beta_k} \equiv < (\beta_k - \beta_k^*)^2 \left| Y_{k-1} \right. > . \tag{27}$$

Through the same calculation process as the estimation algorithm in Section 2, a practical estimation method is derived. Furthermore, considering the system equation of the specific signal in (1) and the dynamical model of the parameters in (24), the prediction algorithm can be derived. The estimation algorithm by applying the proposed noise cancellation method to actual electromagnetic environment is illustrated in Fig. 3 as a flow chart.

The proposed method is applied to estimate the magnetic field leaked from a VDT in the actual office environment of using four computers as shown in Fig. 4. The magnetic field strength leaked from a specific computer denoted by ① is estimated by regarding

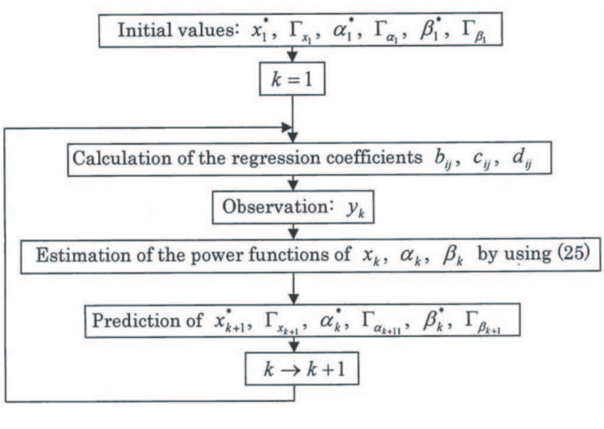

Figure 3. Flow chart of the estimation algorithm by the proposed noise cancellation method.

the magnetic field from other three computers as background noise. The statistics of the specific signal and the background noise are shown in Table 1. Fig. 5 shows the estimated results of the specific signal. For reasons of comparison, the result obtained by the well-known extended Kalman filter [11] based on the Gaussian distribution is also shown in this figure, as a trial. The estimation results using the proposed method based on the Laguerre polynomial connected with Gamma distribution show good agreement with the true values in spite of artificially employing several types of arbitrary initial values. The result from the extended Kalman filter, on the other hand, fluctuates around the true values and shows relatively large estimation error. The corresponding root-mean squared errors of the estimation by the proposed method in three kinds of initial values and the extended Kalman filter are shown in Table 2. From this table, we can find numerically that the proposed method shows more accurate estimation than the result by the extended Kalman filter. The proposed estimation algorithm utilizes recursively the observation data. Therefore, though the estimates sometimes show large estimation error in the case when the signal suddenly changes, the estimation algorithm can recover rapidly the stability according to obtaining new observation data. Moreover, the proposed method can apply to complex situation of the EM sources without the restriction of uniformity and symmetry like Fig. 4.

The above results clearly show the effectiveness of the proposed method for application to the observation contaminated by the background noise.

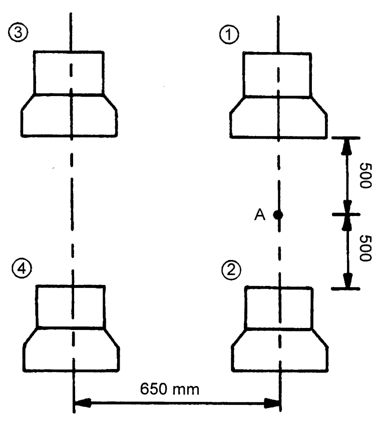

Figure 4. A schematic drawing of the experiment.

Table 1. Statistics of the specific signal and the background noise.

Statistics of specific signal		Statistics of background noise	
Mean [A/m]	Standard Deviation [A/m]	Mean [A/m]	Standard Deviation [A/m]
12.1	0.0310	9.11	0.110

Table 2. Root mean squared error for the estimation of magnetic field (in A/m).

Proposed Method (Initial value: $\hat{x}_0$ [A/m])	Extended Kalman Filter
0.0901 (14.0)	0.162
0.0475 (12.0)	
0.0568 (10.0)	

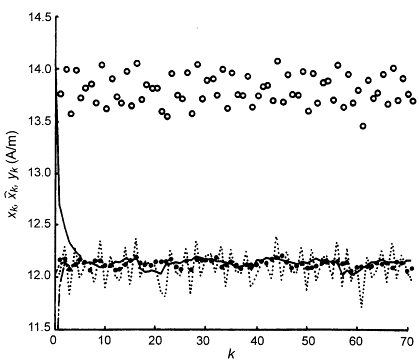

Figure 5. Estimated results by the proposed method (—; $\hat{x}_0 = 14$ [A/m], $- \cdot -$; $\hat{x}_0 = 12$ [A/m], $- \cdot \cdot -$; $\hat{x}_0 = 10$ [A/m]) and by the extended Kalman filter (...), (∘; observed data, • true values).

5. CONCLUSION

In this study, we investigated the random signal in an actual electromagnetic environment. More specifically, a dynamic method for estimating the specific signal based on the noisy observation data contaminated by the background noise was theoretically established. By applying the well known least mean squared method, simplified estimation algorithm was derived. The validity and usefulness of the proposed theory were experimentally confirmed by applying it to the actual magnetic field environment.

The proposed approach is obviously quite different from the ordinary approach, and it is still at an early stage of study. Thus there are a number of problems to be investigated in the future, building on the results of the basic study in this paper. Some of the problems are shown in the following. (i) The proposed method should be applied to other estimation problems in electromagnetic environment, and the practical usefulness should be verified in these situations. (ii) The proposed theory should be extended further to more complicated situations involving multi-signal sources. (iii) In order to estimate more precisely the specific signal, it is essential to consider the higher order statistics in the algorithm of power functional form given by (3) and (25). From a theoretical viewpoint, the proposed algorithm can be constructed with higher precision, by employing many of the power functions of higher order. From a practical viewpoint, however, reliability tends to be lower for the higher order statistics. It is necessary then to investigate up to what order the power functions can be reasonably determined, based on the non-Gaussian property of the phenomena. (iv) The proposed method should be applied to other fields such as noise cancellation in speech recognition and evaluation of sound environment under existence of background noise of non-Gaussian property.

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APPENDIX A. COMUPUTER SIMULATION

We focus our attention on the specific signal x_k with non-Gaussian properties, describing the following system and observation equations:

$$x_{k+1} = 0.8x_k + 5u_k,\ y_k = x_k + cv_k. \tag{A1}$$

Random numbers of the uniform distribution are used as u_k and v_k. The coefficient c denotes a parameter to adjust the magnitude of the external noise v_k. A comparison between two estimated results considering non-Gaussian property and assuming Gaussian property (i.e., $< H_3((x_k - x_k^*)/\sqrt{\Gamma_k})|Y_{k-1} >=< H_3((y_k - y_k^*)/\sqrt{\Omega_k})|Y_{k-1} >=< H_3((v_k - \bar{v}_k)/\sqrt{R_k}) >= 0$ in the regression coefficients of (9)–(14)), is shown in Fig. A1, in the case of the parameter $c = 11$ and the initial value of estimation: $\hat{x}_0 = 30$. The results estimated by considering non-Gaussian property show better agreement with the true values than the results in the case of assuming Gaussian property. The root-mean squared errors of the estimation in several values of the parameter c and several initial values are shown in Table A1. In all cases, the estimates considering non-Gaussian property show more accurate estimation than the results assuming Gaussian property.

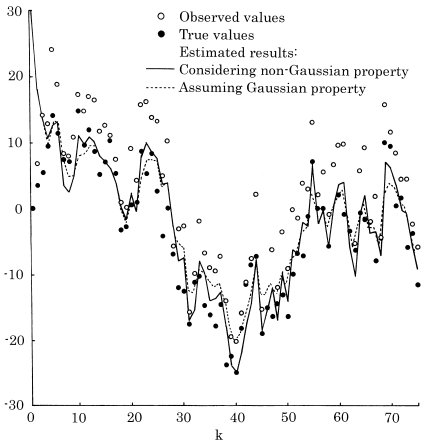

Figure A1. Comparison between two estimated results in the case when $c = 11$ and $\hat{x}_0 = 30$.

Table A1. Root mean squared error of the estimation.

c	Initial value	Considering non-Gaussian property	Assuming Gaussian property
5	10	1.749	1.775
5	20	2.679	2.694
5	30	3.748	3.758
8	10	2.368	2.380
8	20	3.187	3.188
8	30	4.168	4.205
11	10	2.779	2.935
11	20	3.637	3.701
11	30	4.639	4.711

APPENDIX B. REGRESSION COEFFICIENTS OF (25)

$$b_{10} = x_k^*,\ b_{11} = -\frac{\Gamma_{x_k}}{y_k^*},\ b_{20} = \Gamma_{x_k} + (x_k^*)^2,$$

$$b_{21} = -\frac{2(s_{x_k}^*)^3 \left(1 + m_{x_k}^*\right) m_{x_k}^*}{y_k^*},$$

$$b_{22} = \frac{< x_k^2 L_2^{(m_k^*-1)}\left(\frac{y_k}{s_k^*}\right)\left|Y_{k-1}\right. >}{< \left\{L_2^{(m_k^*-1)}\left(\frac{y_k}{s_k^*}\right)\right\}^2 \left|Y_{k-1}\right. >}. \tag{B1}$$

$$c_{10} = \alpha_k^*,\ c_{11} = 0,\ c_{20} = \Gamma_{\alpha_k} + (\alpha_k^*)^2,\ c_{21} = 0,$$

$$c_{22} = \frac{< \alpha_k^2 L_2^{(m_k^*-1)}\left(\frac{y_k}{s_k^*}\right)|Y_{k-1} >}{< \left\{L_2^{(m_k^*-1)}\left(\frac{y_k}{s_k^*}\right)\right\}^2 \left|Y_{k-1}\right. >}. \tag{B2}$$

$$d_{10} = \beta_k^*,\ d_{11} = -\frac{\Gamma_{\beta_k}}{y_k^*},\ d_{20} = \Gamma_{\beta_k} + (\beta_k^*)^2,$$

$$d_{21} = \frac{\left\{\Gamma_{\beta_k} + (\beta_k^*)^2\right\}\beta_k^* - \left(2 + m_{\beta_k}^*\right)\left(1 + m_{\beta_k}^*\right) m_{\beta_k}^*}{y_k^*},$$

$$d_{22} = \frac{< \beta_k^2 L_2^{(m_k^*-1)}\left(\frac{y_k}{s_k^*}\right)\left|Y_{k-1}\right. >}{< \left\{L_2^{(m_k^*-1)}\left(\frac{y_k}{s_k^*}\right)\right\}^2 \left|Y_{k-1}\right. >}, \tag{B3}$$

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