A NOISE CANCELLATION METHOD IN SOUND AND ELECTROMAGNETIC ENVIRONMENT OF POWER STATE VARIABLES

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ABSTRACT

The observed phenomena in actual sound and electromagnetic environment are inevitably contaminated by the background noise of arbitrary distribution type. Therefore, in order to evaluate sound and electromagnetic environment, it is necessary to establish some estimation methods to remove the undesirable effects of the background noise. In this paper, we propose a noise cancellation method for estimating the power state variables of a specific signal with the existence of background noise of non-Gaussian distribution from two viewpoints of static and dynamic signal processing. 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 estimation problems in actual sound and magnetic field environment.

1. INTRODUCTION

The specific signal in the actual sound and electromagnetic waves frequently shows some very complex fluctuation forms of non-Gaussian type owing to natural, social and human factors[1]. Furthermore, the observed data are inevitably contaminated by the background noise of arbitrary distribution type. In these situations, it is often desirable to estimate several evaluation quantities such as L_{eq} (averaged energy on decibel scale), L_x ((100-x) percentile level, $x = 5$, 10, 50, 90, 95), the peak value, the amplitude probability distribution, the average crossing rate, the pulse spacing and duration distributions, etc. of the specific signal. Without losing their mutual relationship, it is indispensable to estimate the probability distribution or the original wave fluctuation form itself of the specific signal based on the observed noise data.

Hitherto many methodological studies have been reported on the state estimation for stochastic systems[2]. However, many standard estimation methods proposed previously in a study of stochastic systems are restricted only to the Gaussian distribution (in more cases, zero mean). Several state estimation methods for nonlinear system have been also proposed by assuming the Gaussian distribution of system and observation noises[3, 4, 5]. The actual sound and electromagnetic environment often shows an intricate fluctuation pattern rather than the standard Gaussian distribution. For example, since the specific signal in sound environment systems is usually measured by the sound level meter, the sound environment may be very often considered on the power scale as a system with the signal of nonzero mean. So, it becomes essentially a big problem to apply the conventional state estimation methods to the present situation without any improvement on them.

In our previous studies[6, 7], 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, a state estimation method for stochastic systems with unknown structure has been proposed by using Bayes theorem on probability distribution[8]. Since our previously reported estimation algorithms were based on the whole of the probability distribution, their derivation processes became rather complicated.

In this study, static and dynamic signal processing methods for estimating a specific signal with the existence of background noise of non-Gaussian distribution forms are proposed. More specifically, by paying attention to the power state variables for a specific signal in the sound and electromagnetic environment, which exhibits complex probability distribution forms, we propose a new type of signal processing method for estimating a specific signal on a power scale. In the case of considering the power state variables, 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. A Laguerre polynomial is suitable to the power state variables, which fluctuate within only the positive region. The proposed method positively utilizes the additive property of power state variables in the derivation processes of the estimation algorithm. Instead of focusing on the whole of the probability distribution in our previous studies[6, 7, 8], by applying the well-known least mean squared method for the moment statistics with several orders, a simplified estimation algorithm is derived from the practical viewpoint.

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

2. THEORETICAL CONSIDERATION

2.1 Static Noise Cancellation Method for Sound Environment

In the evaluation of sound environment around a main line, it is necessary to estimate the sound levels at plural evaluation points based on the observation at a reference point because of the difficulties of monitoring the sound levels at all evaluation points and at every instantaneous time. Firthermore, in the measurement of sound enviornment, the observation data are generally contaminated by an external noise (i.e., background noise). The power state variables satisfying the additive property of the specific signal and the background noise are considered in this study.

Let x and y be the specific signals in a power scale at an evaluation point and a reference point respectively. The probability distribution of x has to be predicted on the basis of the observed data of y. Though a single evaluation point is considered in the theoretical consideration for the simplification of the mathematical expression, the extension of theory to a case of multi-evaluation points is easy by considering multi-dimensional variable $\mathbf{x}$ instead of single variable x. In order to find explicitly the various statistical properties of x, let us expand the probability density function $P(x)$ into an orthogonal polynomial series, as follows[9]:

$$P(x) = P_0(x)\sum_{n=0}^{\infty} A_n \psi_n(x),\ A_n \equiv <\psi_n(x)>, \quad (1)$$

where <> is an averaging operation with respect to the random variables. In (1), $P_0(x)$ can be artificially chosen as the probability density functions describing the dominant parts of the actual fluctuation pattern. The information on the various types of lower and/or higher order correlations of x is reflected hierarchically in each expansion coefficient A_n. In this study, gamma distribution suiatble for random variables fluctuating within only a positive range such as the specific signal in a power scale is adopted.

$$\begin{aligned} P_0(x) &= \frac{x^{m_x-1}}{\Gamma(m_x)s_x^{m_x}} e^{-\frac{x}{s_x}}, \\ m_x &\equiv \frac{\mu_x^2}{\sigma_x^2},\ s_x \equiv \frac{\sigma_x^2}{\mu_x}, \\ \mu_x &\equiv <x>,\ \sigma_x^2 \equiv <(x-\mu_x)^2>, \end{aligned} \quad (2)$$

where $\Gamma(\ )$ is a Gamma function. Thus, orthogonal polynomial is given by

$$\psi_n(x) = \sqrt{\frac{\Gamma(m_x)n!}{\Gamma(m_x+n)}} L_n^{(m_x-1)}(\frac{x}{s_x}), \quad (3)$$

where $L_n^{(m-1)}(\ )$ is a Laguerre polynomial of n-th order, defined by the following equation[10]:

$$\begin{aligned} L_n^{(m)}(x) &\equiv \frac{e^x x^{-m}}{n!}\frac{d^n}{dx^n}(e^{-x}x^{n+m}) \\ &= \sum_{r=0}^{n}(-1)^r {}_{n+m}C_{n-r}\frac{x^r}{r!}. \end{aligned} \quad (4)$$

In the measurement of sound environment, the effects by a background noise are inevitable. Then, based on the additive property of power state variables, the observed sound power z is expressed as

$$z = x + v, \quad (5)$$

where x and v are the specific signal and a background noise in a power scale at an evaluation point. We assume that the statistics of background noise are known. From (5), the following relationship can be obtained:

$$z^n = (x+v)^n = \sum_{i=0}^{n} {}_nC_i x^{n-i} v^i. \quad (6)$$

In order to derive a prediction method for the probability density function of specific signal x at an evaluation point from observation y at a reference point, we pre-establish the system models on power functions of z, after replacing x^r with the conditional expectation $<x^r|y>$ in (6) by introducing a regression model for $<x^r|y>$ in a linear combination of Laguerre polynomials, as follows:

$$\begin{aligned} \hat{z} &\equiv <x|y> + v = a_{10} + a_{11}L_1(Y) + v, \\ \hat{z^2} &\equiv <x^2|y> + 2<x|y>v + v^2 \\ &= a_{20} + a_{21}L_1(Y) + a_{22}L_2(Y) \\ &\quad +2\{a_{10} + a_{11}L_1(Y)\}v + v^2, \\ \hat{z^3} &\equiv <x^3|y> + 3<x^2|y>v \\ &\quad +3<x|y>v^2 + v^3 \\ &= a_{30} + a_{31}L_1(Y) + a_{32}L_2(Y) + a_{33}L_3(Y) \\ &\quad +3\{a_{20} + a_{21}L_1(Y) + a_{22}L_2(Y)\}v \\ &\quad +3\{a_{10} + a_{11}L_1(Y)\}v^2 + v^3, \\ &\quad \cdots\cdots\cdots\cdots \end{aligned} \quad (7)$$

with

$$L_n(Y) \equiv L_n^{(m_y-1)}(y/s_y), \quad (8)$$

where $a_{ij}(i=1,2,3,\cdots;j=0,1,2,\cdots,i)$ in (7) are regression coefficients, and estimated by applying the well-known least squared method for the moment statistics with several orders. More specifically, the regression coefficients in (7) are decided so as to minimize the criteria:

$$\begin{aligned} I_1 &= <(z-\hat{z})^2> \rightarrow Minimize, \\ I_2 &= <(z^2-\hat{z^2})^2> \rightarrow Minimize, \\ I_3 &= <(z^3-\hat{z^3})^2> \rightarrow Minimize, \\ &\cdots\cdots\cdots\cdots\cdots\cdots\cdots. \end{aligned} \quad (9)$$

From $\partial I_1/\partial a_{10} = \partial I_1/\partial a_{11} = \partial I_2/\partial a_{20} = \partial I_2/\partial a_{21} = \partial I_2/\partial a_{22} = \partial I_3/\partial a_{30} = \partial I_3/\partial a_{31} = \cdots = 0$, the coefficients $a_{10}, a_{11}, a_{20}, a_{21}, \cdots$, are derived.

Next, by using the estimated regression coefficients, the moment statistics with several orders of the specific signal x at the evaluation point can be predicted on the basis of arbitrary observation data y at the reference point, as follows:

$$\begin{aligned} <x> &= << x|y>>_y = a_{10} + a_{11} < L_1(Y)>, \\ <x^2> &= << x^2|y>>_y \\ &= a_{20} + a_{21} < L_1(Y)> + a_{22} < L_2(Y)>, \\ <x^3> &= << x^3|y>>_y \\ &= a_{30} + a_{31} < L_1(Y)> + a_{32} < L_2(Y)> \\ &\quad + a_{33} < L_3(Y)>, \\ &\quad \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots. \end{aligned} \quad (10)$$

After evaluating two parameters m_x, s_x and expansion coefficients A_n by use of (10), as

$$m_x = \frac{<x>^2}{<x^2> - <x>^2}, \quad (11)$$

$$s_x = \frac{<x^2> - <x>^2}{<x>}, \quad (12)$$

$$A_n = \sqrt{\frac{\Gamma(m_x)n!}{\Gamma(m_x+n)}} \sum_{r=0}^{n} (-1)^r {}_{n+m}C_{n-r} \frac{<x^r>}{r!}. \quad (13)$$

by substituting (11)-(13) into (1)-(3), the probability density function connected with several evaluation quantities for sound environment can be predicted.

2.2 Dynamic Noise Cancelation Method for Sound and Electromagnetic Environment

Let us consider the sound and electromagnetic environment with the power state variables fluctuating in a non-stationary form within a positive region, and express the system equation as:

$$x_{k+1} = Fx_k + Gu_k, \quad (14)$$

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[11]. 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:

$$y_k = x_k + v_k. \quad (15)$$

Because the statistics of the background noise are often unknown, the following noise model is introduced.

$$v_k = \alpha_k e_k + \beta_k, \quad (16)$$

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, the simple dynamical model is introduced.

$$\alpha_{k+1} = \alpha_k, \ \beta_{k+1} = \beta_k. \quad (17)$$

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 functions of x_k. Since the parameters α_k and β_k are also unknown, 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):

$$\begin{aligned} \hat{x}_k &= b_{10} + b_{11} L_1^{(m_k^*-1)}(\frac{y_k}{s_k^*}), \\ \hat{x_k^2} &= b_{20} + b_{21} L_1^{(m_k^*-1)}(\frac{y_k}{s_k^*}) + b_{22} L_2^{(m_k^*-1)}(\frac{y_k}{s_k^*}), \\ \hat{\alpha}_k &= c_{10} + c_{11} L_1^{(m_k^*-1)}(\frac{y_k}{s_k^*}), \\ \hat{\alpha_k^2} &= c_{20} + c_{21} L_1^{(m_k^*-1)}(\frac{y_k}{s_k^*}) + c_{22} L_2^{(m_k^*-1)}(\frac{y_k}{s_k^*}), \\ \hat{\beta}_k &= d_{10} + d_{11} L_1^{(m_k^*-1)}(\frac{y_k}{s_k^*}), \\ \hat{\beta_k^2} &= d_{20} + d_{21} L_1^{(m_k^*-1)}(\frac{y_k}{s_k^*}) + d_{22} L_2^{(m_k^*-1)}(\frac{y_k}{s_k^*}), \end{aligned} \quad (18)$$

where $\hat{x}_k, \hat{x_k^2}, \hat{\alpha}_k, \hat{\alpha_k^2}, \hat{\beta}_k, \hat{\beta_k^2}$ denote the estimates of $x_k, x_k^2, \alpha_k, \alpha_k^2, \beta_k, \beta_k^2$ respectively. Furthermore, b_{ij}, c_{ij} and d_{ij} denote the regression coefficients.

Considering (15) and (16), two parameters m_k^* and s_k^* can be given by

$$\begin{aligned} m_k^* &\equiv \frac{(y_k^*)^2}{\Omega_k}, \ s_k^* \equiv \frac{\Omega_k}{y_k^*}, \\ y_k^* &\equiv < y_k|Y_{k-1}> = x_k^* + \beta_k^*, \\ \Omega_k &\equiv <(y_k - y_k^*)^2|Y_{k-1}> \\ &= \Gamma_{x_k} + \Gamma_{\alpha_k} + \Gamma_{\beta_k} + (\alpha_k^*)^2 \end{aligned} \quad (19)$$

with

$$
\begin{aligned}
x_k^* &\equiv < x_k|Y_{k-1} >,\ \Gamma_{x_k} \equiv < (x_k - x_k^*)^2|Y_{k-1} >,\\
\alpha_k^* &\equiv < \alpha_k|Y_{k-1} >,\ \Gamma_{\alpha_k} \equiv < (\alpha_k - \alpha_k^*)^2|Y_{k-1} >,\\
\beta_k^* &\equiv < \beta_k|Y_{k-1} >,\ \Gamma_{\beta_k} \equiv < (\beta_k - \beta_k^*)^2|Y_{k-1} >,
\end{aligned}
\tag{20}
$$

where $Y_{k-1}(=\{y_1, y_2, \cdots, y_{k-1}\})$ is a set of observation data up to a time $k-1$.

Next, by applying the well-known least mean squared method for the moment statistics with first and second orders, a practical estimation method is derived. More specifically, the regression coefficients in (18) are decided so as to minimize the criteria:

$$
\begin{aligned}
J_1 &= < (x_k - \hat{x}_k)^2|Y_{k-1} > \rightarrow Minimize,\\
J_2 &= < (x_k^2 - \hat{x_k^2})^2|Y_{K-1} > \rightarrow Minimize,\\
J_3 &= < (\alpha_k - \hat{\alpha}_k)^2|Y_{k-1} > \rightarrow Minimize,\\
& \cdots\cdots\cdots\cdots\cdots\cdots\cdots.
\end{aligned}
\tag{21}
$$

After substituting (18) in (21) and differentiating it with respect to each regression coefficient, and then using the statistical property of Laguerre polynomial, the regression coefficients can be expressed in functional forms of $x_k^*, \Gamma_{x_k}, \alpha_k^*, \Gamma_{\alpha_k}, \beta_k^*, \Gamma_{\beta_k}$.

Finally, by considering (14) and (17), the prediction algorithm essential for performing the recursive estimation can be expressed as

$$
\begin{aligned}
x_{k+1}^* &= F\hat{x}_k + G < u_k >,\\
\alpha_{k+1}^* &= \hat{\alpha}_k,\ \beta_{k+1}^* = \hat{\beta}_k,\\
\Gamma_{x_{k+1}} &= F^2\{\hat{x_k^2} - (\hat{x}_k)^2\}\\
&\quad + G^2 < (u_k - < u_k >)^2 >,\\
\Gamma_{\alpha_{k+1}} &= \hat{\alpha_k^2} - (\hat{\alpha}_k)^2,\ \Gamma_{\beta_{k+1}} = \hat{\beta_k^2} - (\hat{\beta}_k)^2.
\end{aligned}
\tag{22}
$$

Therefore, by combining the estimation algorithm of (18) with the prediction algorithm of (22), the recurrence estimation of the specific signal can be achieved.

3. EXPERIMENTAL CONSIDERATION

The effectiveness of the proposed static signal processing method in Sect. 2.1 is confirmed experimentally by applying it to actual road traffic noise data observed in a complicated sound environment near a national road. In order to evaluate the sound environment around the main line, the sound level at an evaluation point has to be predicted on the basis of the observation at a reference point. The reference point and the evaluation point were chosen at the positions being 1 m and 25 m apart from one side of the road. One of the predicted results is shown in Fig. 1. The theoretically predicted curves of the 2nd and 3rd approximations considering up to the third and fourth order moments of x in (10) show precise agreements with the experimentally sampled values for the probability distribution of the road traffic noise at the evaluation point.

Next, in order to examine the practical usefulness of the proposed dynamic signal processing method in Sect. 2.2, it is applied to the actual state estimation problem in specific sound and magnetic field environment. Actual road traffic noise is adopted as an example of a specific signal with a complex fluctuation form. Applying the proposed estimation method to actually observed data contaminated by background noise, the fluctuation wave form of the specific signal (i.e., road traffic noise) was estimated. Figures 2 shows one of the estimated results for the road traffic noise. For reasons of comparison, the results obtained by the well-known extended Kalman filter[3] are also shown in this figure. It is noted that the proposed method estimates fairly precisely the specific signal with rapidly changing fluctuations. The results from the extended Kalman filter, on the other hand, show relatively large estimation errors, particularly in the estimation of the lower level values of the fluctuation, in which the specific signal is completely embedded in the background noise.

Furthermore, 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 under the situation of playing a computer game. More specifically, in the actual office environment of using four computers, the magnetic field strength leaked from a specific computer is estimated by regarding the magnetic field from other three computers 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 obervation data were obtained. Figure 3 shows the estimated results of the specific signal. The estimation results using the proposed method show good agreement with the true values in spite of artificially employing several types of arbitrary initial values.

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

4. CONCLUSION

In this study, we investigated the random signal on a power scale in an actua sound and electromagnetic environment fluctuating within the positive region. First, a static method for predicting the probability distribution of the specific signal at a evaluation point was proposed on the basis of observation at a reference point in sound environment. Furthermore, a dynamic method for esti-

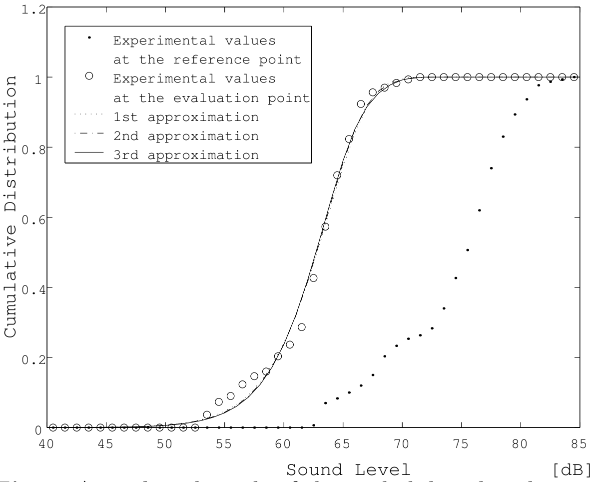

Fig. 1 A predicted result of the probability distribution at an evaluation point.

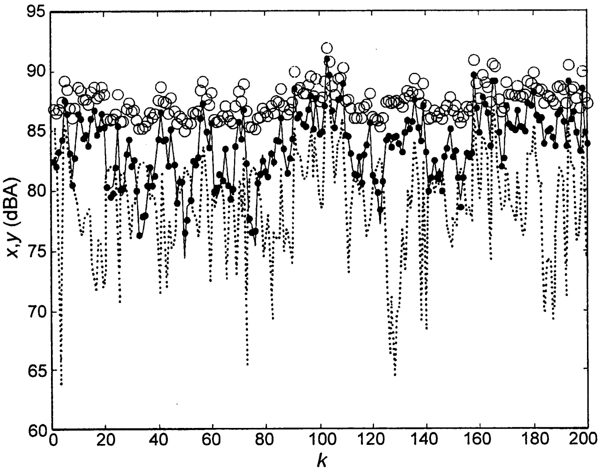

Fig. 2 Estimation results of the fluctuation of the road traffic noise (○; observed data, • ; true values, —; estimated result by the proposed method, ···; estimated result by the extended Kalman filter).

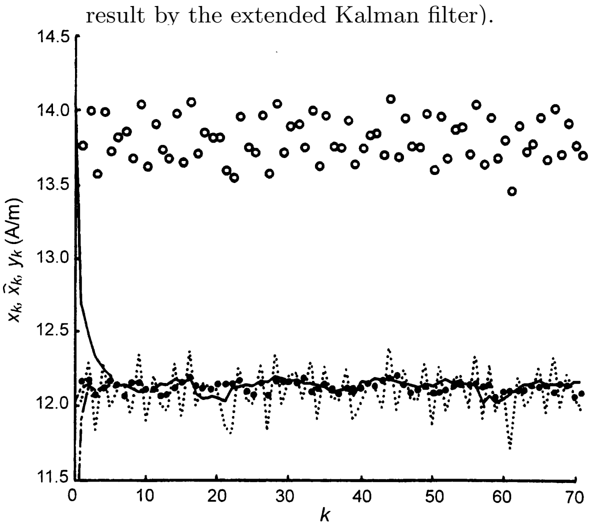

Fig. 3 Estimated results (○; observed data, •; true values, by the proposed method (—; $\hat{x}_0 = 14$A/m, $-\cdot-$; $\hat{x}_0 = 12$A/m, $-\cdot\cdot-$; $\hat{x}_0 = 10$A/m) and by the extended Kalman filter (···).

mating the specific signal based on the noisy observation data contaminated by the background noise was theoretically established in a realistic situation when the statistics of the background noise were unknown. By applying the well known least mean squared method, simplified prediction and estimation algorithms were derived. The validity and usefulness of the proposed theory were experimentally confirmed by applying it to the actual sound and magnetic field environment.

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