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STATE ESTIMATION METHOD FOR SOUND ENVIRONMENT SYSTEM WITH UNKNOWN STRUCTURE AND ITS APPLICATION TO EVALUATION OF ROAD TRAFFIC NOISE

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Abstract

The actual sound environment system exhibits various types of linear and non-linear characteristics, and it often contains an unknown structure. Furthermore, the observations in the sound environment are often in the level-quantized form. In this paper, a method for estimating the specific signal for stochastic systems with unknown structure and the quantized observation is proposed by introducing a system model of the conditional probability type. The effectiveness of the proposed theoretical method is confirmed by applying it to the actual problem of psychological evaluation for road traffic noise.

1. INTRODUCTION

The internal physical mechanism of actual sound environment system is often difficult to recognize analytically, and it contains unknown structural characteristics. Furthermore, the stochastic process observed in the actual phenomenon exhibits complex fluctuation pattern and there exist potentially various nonlinear correlations in addition to the linear correlation between input and output time series.

In our previous study, for complex sound environment systems difficult to analyze by using usual structural methods based on the physical mechanism, a nonlinear system model was derived in the expansion series form reflecting various type correlation information from the higher order to the higher order between input and output variables [1]. The conditional probability density function contains the linear and nonlinear correlations in the expansion coefficients, and these correlations play an important role as the statistical information for the input and output relationship.

In this paper, a complex sound environment system including the human consciousness and response for physical sound phenomena is considered. It is necessary to pay our attention on the fact that the observation data in the sound environment system are often measured in a level-quantized form. For example, the human psychological evaluation for noise annoyance can be judged by use of 7 levels from 1. very calm to 7. very noisy [2]. Furthermore, the observation data are often measured in a digital level form at discrete times because various kinds of statistical evaluation (e.g., median, mean, covariance, higher order moments, etc.) for these quantized level data become easier if a digital computer is used. In this situation, in order to evaluate the objective sound environment system, it is desirable to estimate the waveform fluctuation of the specific signal based on the observed data with quantized level.

From the above viewpoint, based on the quantized observations, a method for estimating precisely the specific signal for the sound environment system with unknown structural characteristic is theoretically proposed in this study. More specifically, by adopting an expansion expression of the conditional probability distribution reflecting the various information on linear and non-linear correlation between the specific signal and the quantized observation as the system characteristics, a method to estimate the time series of the specific signal is theoretically derived. The proposed estimation method can be applied to an actual complex sound environment system with unknown structure by considering the coefficients of conditional probability distribution as unknown parameters and estimating simultaneously these parameters and the specific signal. The proposed method can be applied to several state estimation problems for stochastic systems with unknown structure in engineering field. For example, this method can be applied to the estimation of the output signal for information and communication systems with unknown system characteristics based on the noisy observation of the input signal. Furthermore, this method can be also applied to the blind estimation for unknown systems based on the noisy output. As one of applications, the proposed theory is applied to the estimation problem of the psychological evaluation for road traffic noise and the effectiveness of the theory is experimentally confirmed.

2. STOCHASTIC MODEL FOR SOUND ENVIRONMENT SYSTEM WITH UNKNOWN STRUCTURE

Consider a complex sound environment system with an unknown structure that can not be obtained on the basis of the internal physical mechanism of the system. In the observations of actual sound environment system, the sound level data are very often measured in a digital level form at discrete times. This is because some signal processing methods by utilizing a digital computer are indispensable for extracting exactly various kinds of evaluation quantities based on these quantized level data.

Let x_k and y_k be the specific signal and quantized observation at a discrete time k. It is assumed that there are complex nonlinear relationships between x_k and y_k, which are difficult to find the fundamental relationships between them. A method to estimate x_k based on the quantized observation y_k is derived in this study. Since the system characteristics are unknown, a system model in the form of a conditional probability is adopted. More precisely, attention is focused on the conditional probability distribution function $P(y_k \mid x_k)$ reflecting all linear and non-linear correlation information between x_k and y_k.

Expanding the joint probability distribution function $P(x_k, y_k)$ in an orthogonal form based on the product of $P(x_k)$ and $P(y_k)$, the following expression on the conditional probability distribution function can be derived.

$$P(y_k \mid x_k) = P(y_k) \sum_{r=0}^{R} \sum_{s=0}^{S} A_{rs} \theta_r^{(1)}(x_k) \theta_s^{(2)}(y_k),$$

$$A_{rs} = <\theta_r^{(1)}(x_k) \theta_s^{(2)}(y_k)>, \tag{1}$$

where < > denotes the averaging operation on the variables. The linear and non-linear correlation information between x_k and y_k is reflected hierarchically by each expansion coefficient A_{rs}. The functions $\theta_r^{(1)}(x_k)$ and $\theta_s^{(2)}(y_k)$ are orthonormal polynomials with the weighting functions $P(x_k)$ and $P(y_k)$ respectively, and satisfy the following orthonormal conditions:

$$\int \theta_r^{(1)}(x_k)\theta_{r'}^{(1)}(x_k)P(x_k)dx_k = \delta_{rr'}\,, \tag{2}$$

$$\sum_{y_k} \theta_s^{(2)}(y_k)\theta_{s'}^{(2)}(y_k)P(y_k) = \delta_{ss'}\,. \tag{3}$$

These orthonormal polynomials can be decomposed by using Schmidt's orthogonalization [3]. Though (1) is originally an infinite series expansion, a finite expansion series with $r \le R$ and $s \le S$ is adopted because only finite expansion coefficients are available and the consideration of the expansion coefficients from the first few terms is usually sufficient in practice. Since the objective system involves an unknown specific signal, unknown structure and unknown observation noise, the expansion coefficients A_{rs} expressing hierarchically the statistical relationship between the specific signal and observation must be estimated on the basis of the noisy observation y_k. Considering the expansion coefficients A_{rs} as unknown parameter vector $\mathbf{a}$:

$$\begin{aligned} &\mathbf{a} \equiv (a_1,\ a_2,\ \ldots,\ a_I) \equiv (\mathbf{a}_{(1)},\ \mathbf{a}_{(2)},\ \ldots,\ \mathbf{a}_{(S)}), \\ &\mathbf{a}_{(s)} \equiv (A_{1s},\ A_{2s},\ \ldots,\ A_{Rs}),\ \ (s = 1,\ 2,\ \ldots,\ S), \end{aligned} \tag{4}$$

the following simple dynamical model is naturally introduced for the simultaneous estimation of the parameters with the specific signal x_k:

$$\begin{aligned} &\mathbf{a}_{k+1} = \mathbf{a}_k\,, \\ &(\mathbf{a}_k \equiv (a_{1,k},\ a_{2,k},\ \ldots,\ a_{I,k}) \equiv (\mathbf{a}_{(1),k},\ \mathbf{a}_{(2),k},\ \ldots,\ \mathbf{a}_{(S),k}))\,, \end{aligned} \tag{5}$$

where $I\ \ (= R \cdot S)$ is the number of unknown expansion coefficients to be estimated.

On the other hand, based on the correlative property in time domain for the specific signal fluctuating with non-Gaussian property, the following time transition model for the specific signal is generally established.

$$x_{k+1} = Fx_k + Gu_k\,, \tag{6}$$

where u_k is the random input with mean 0 and variance σ_u^2. Two parameters F and G are estimated by using an auto-correlation technique [3].

3. DERIVATION OF STATE ESTIMATION ALGORITHM

To derive an estimation algorithm for the specific signal x_k, attention is focused on Bayes' theorem for the conditional probability distribution [3, 4]. Since the parameter $\mathbf{a}_k$ is also unknown, the conditional probability density function of x_k and $\mathbf{a}_k$ is considered.

$$P(x_k, \mathbf{a}_k \mid Y_k) = \frac{P(x_k, \mathbf{a}_k, y_k \mid Y_{k-1})}{P(y_k \mid Y_{k-1})}\,, \tag{7}$$

where Y_k is a set of observation data up to time k. The conditional joint probability distribution $P(x_k, \mathbf{a}_k, y_k \mid Y_{k-1})$ can be generally expanded in a statistical orthogonal expansion series

$$\begin{aligned} P(x_k, \mathbf{a}_k, y_k \mid Y_{k-1}) &= P_0(x_k \mid Y_{k-1})P_0(\mathbf{a}_k \mid Y_{k-1})P_0(y_k \mid Y_{k-1}) \\ &\quad \sum_{l=0}^{\infty}\sum_{\mathbf{m}=\mathbf{0}}^{\infty}\sum_{n=0}^{\infty} B_{l\mathbf{m}n}\ \varphi_l^{(1)}(x_k)\varphi_{\mathbf{m}}^{(2)}(\mathbf{a}_k)\varphi_n^{(3)}(y_k) \end{aligned} \tag{8}$$

with

$$B_{l\mathbf{m}n} = \langle \varphi_l^{(1)}(x_k)\varphi_{\mathbf{m}}^{(2)}(\mathbf{a}_k)\varphi_n^{(3)}(y_k) \mid Y_{k-1} \rangle\,. \tag{9}$$

After substituting (8) into (7) and expanding an arbitrary polynomial function $f_{L,\mathbf{M}}(x_k, \mathbf{a}_k)$ of x_k and $\mathbf{a}_k$ with the ($L, \mathbf{M}$)th order in a series expansion form using $\{\varphi_l^{(1)}(x_k)\}$ and

$\{\varphi_{\mathbf{m}}^{(2)}(\mathbf{a}_k)\}$:

$$f_{L,\mathbf{M}}(x_k,\mathbf{a}_k)=\sum_{l=0}^{L}\sum_{\mathbf{m}=\mathbf{0}}^{\mathbf{M}}C_{l\mathbf{m}}^{L\mathbf{M}}\varphi_l^{(1)}(x_k)\varphi_{\mathbf{m}}^{(2)}(\mathbf{a}_k),\quad (C_{l\mathbf{m}}^{L\mathbf{M}}\text{; appropriate constants}), \tag{10}$$

by taking the conditional expectation of the function $f_{L,\mathbf{M}}(x_k,\mathbf{a}_k)$ and using the orthonormal condition for the functions $\varphi_l^{(1)}(x_k)$ and $\varphi_{\mathbf{m}}^{(2)}(\mathbf{a}_k)$, the estimate of the function $f_{L,\mathbf{M}}(x_k,\mathbf{a}_k)$ can be derived as an infinite series expression, as:

$$\hat{f}_{L,\mathbf{M}}(x_k,\mathbf{a}_k)\equiv< f_{L,\mathbf{M}}(x_k,\mathbf{a}_k)\,|\,Y_k >$$

$$=\frac{\sum_{l=0}^{L}\sum_{\mathbf{m}=\mathbf{0}}^{\mathbf{M}}\sum_{n=0}^{\infty}C_{l\mathbf{m}}^{L\mathbf{M}}B_{l\mathbf{m}n}\varphi_n^{(3)}(y_k)}{\sum_{n=0}^{\infty}B_{0\mathbf{0}n}\varphi_n^{(3)}(y_k)}. \tag{11}$$

The three functions $\varphi_l^{(1)}(x_k)$, $\varphi_{\mathbf{m}}^{(2)}(\mathbf{a}_k)$ and $\varphi_n^{(3)}(y_k)$ are orthonormal polynomials of degrees l, $\mathbf{m}\equiv(m_1,\ m_2,\ ...,\ m_I)$ and n with weighting functions $P_0(x_k\,|\,Y_{k-1})$, $P_0(\mathbf{a}_k\,|\,Y_{k-1})$ and $P_0(y_k\,|\,Y_{k-1})$, which can be chosen as the probability function describing the above dominant parts of the actual fluctuation or as standard probability distribution.

As an example of standard probability functions for the specific signal and the parameter, consider the Gaussian distribution:

$$P_0(x_k\,|\,Y_{k-1})=\frac{1}{\sqrt{2\pi\Gamma_{x_k}}}e^{-\frac{(x_k-x_k^*)^2}{2\Gamma_{x_k}}},$$

$$x_k^*=< x_k\,|\,Y_{k-1}>,\quad \Gamma_{x_k}=<(x_k-x_k^*)^2\,|\,Y_{k-1}>, \tag{12}$$

$$P_0(\mathbf{a}_k\,|\,Y_{k-1})=\prod_{i=1}^{I}\frac{1}{\sqrt{2\pi\Gamma_{a_{i,k}}}}e^{-\frac{(a_{i,k}-a_{i,k}^*)^2}{2\Gamma_{a_{i,k}}}},$$

$$a_{i,k}^*=< a_{i,k}\,|\,Y_{k-1}>,\quad \Gamma_{a_{i,k}}=<(a_{i,k}-a_{i,k}^*)^2\,|\,Y_{k-1}>. \tag{13}$$

Furthermore, as the fundamental probability function on the level-quantized observation, the generalized binomial distribution [5] with level difference interval h_y can be chosen:

$$P_0(y_k\,|\,Y_{k-1})=\frac{(\frac{N_k-y_M}{h_y})!}{(\frac{y_k-y_M}{h_y})!(\frac{N_k-y_k}{h_y})!}\,p_k^{\frac{y_k-y_M}{h_y}}(1-p_k)^{\frac{N_k-y_k}{h_y}},$$

$$p_k=\frac{y_k^*-y_M}{N_k-y_M},\quad y_k^*=< y_k\,|\,Y_{k-1}>,$$

$$N_k=\frac{(y_k^*-y_M)h_y y_k^*-y_M\Omega_{y_k}}{(y_k^*-y_M)h_y-\Omega_{y_k}},\quad \Omega_{y_k}=<(y_k-y_k^*)^2\,|\,Y_{k-1}>, \tag{14}$$

where y_M is the minimum level of observations. The orthonormal polynomials with three weighting probability distributions in (12)-(14) can be determined as

$$\varphi_l^{(1)}(x_k)=\frac{1}{\sqrt{l!}}H_l\left(\frac{x_k-x_k^*}{\sqrt{\Gamma_{x_k}}}\right), \tag{15}$$

$$\varphi_{\mathbf{m}}^{(2)}(\mathbf{a}_k)=\prod_{i=1}^{I}\frac{1}{\sqrt{m_i}}H_{m_i}(\frac{a_{i,k}-a_{i,k}^{*}}{\sqrt{\Gamma_{a_i}}})\ , \tag{16}$$

$$\varphi_n^{(3)}(y_k)=\{(\frac{N_k-y_M}{h_y})^{(n)}n!\}^{-1/2}(\frac{1-p_k}{p_k})^{n/2}\frac{1}{h_y^n}$$
$$\cdot\sum_{j=0}^{n}\binom{n}{j}(-1)^{n-j}(\frac{p_k}{1-p_k})^{n-j}(N_k-y_k)^{(n-j)}(y_k-y_M)^{(j)}, \tag{17}$$

where $H_l(\bullet)$ denotes the Hermite polynomial with l th order, and $y^{(j)}$ is the j th order factorial function defined by [5]

$$y^{(n)}=y(y-h_y)(y-2h_y)\cdots(y-(n-1)h_y),\quad y^{(0)}=1. \tag{18}$$

In two special cases when $f_{1,\mathbf{0}}(x_k,\mathbf{a}_k)=x_k$, $f_{2,\mathbf{0}}(x_k,\mathbf{a}_k)=(x_k-\hat{x}_k)^2$, estimates related to mean and variance of the state variable are expressed as follows:

$$\hat{x}_k=<x_k\,|\,Y_k>$$
$$=\frac{\sum_{n=0}^{\infty}\left\{B_{0\mathbf{0}n}C_{\mathbf{00}}^{1\mathbf{0}}+B_{1\mathbf{0}n}C_{1\mathbf{0}}^{1\mathbf{0}}\right\}\varphi_n^{(3)}(y_k)}{\sum_{n=0}^{\infty}B_{0\mathbf{0}n}\varphi_n^{(3)}(y_k)}, \tag{19}$$

$$P_{x_k}=<(x_k-\hat{x}_k)^2\,|\,Y_k>$$
$$=\frac{\sum_{n=0}^{\infty}\left\{B_{0\mathbf{0}n}C_{0\mathbf{0}}^{2\mathbf{0}}+B_{1\mathbf{0}n}C_{1\mathbf{0}}^{2\mathbf{0}}+B_{2\mathbf{0}n}C_{2\mathbf{0}}^{2\mathbf{0}}\right\}\varphi_n^{(3)}(y_k)}{\sum_{n=0}^{\infty}B_{0\mathbf{0}n}\varphi_n^{(3)}(y_k)} \tag{20}$$

with

$$C_{0\mathbf{0}}^{1\mathbf{0}}=x_k^{*}\ ,\quad C_{1\mathbf{0}}^{1\mathbf{0}}=\sqrt{\Gamma x_k}\ ,$$
$$C_{0\mathbf{0}}^{2\mathbf{0}}=\Gamma x_k+\left(x_k^{*}-\hat{x}_k\right)^2,\quad C_{1\mathbf{0}}^{2\mathbf{0}}=2\sqrt{\Gamma x_k}\left(x_k^{*}-\hat{x}_k\right),\quad C_{2\mathbf{0}}^{2\mathbf{0}}=\sqrt{2}\Gamma x_k. \tag{21}$$

Using the property of conditional expectation and (2), the two variables y_k^{*} and Ω_{y_k} in (14) can be expressed in functional forms on predictions of x_k and $\mathbf{a}_k$ at a discrete time $k-1$ (i.e. the expectation value of arbitrary functions of x_k and $\mathbf{a}_k$ conditioned by Y_{k-1}), as follows:

$$y_k^{*}=<<y_k\,|\,x_k,Y_{k-1}>|\,Y_{k-1}>$$
$$=<\sum_{y_k}y_kP(y_k\,|\,x_k)\,|\,Y_{k-1}>$$
$$=<\sum_{r=0}^{\infty}\sum_{s=0}^{1}d_{1s}A_{rs}\theta_r^{(1)}(x_k)\,|\,Y_{k-1}>$$
$$=\sum_{s=0}^{1}d_{1s}<\mathbf{A}_{(s),k}\Theta(x_k)\,|\,Y_{k-1}>, \tag{22}$$

$$\Omega_{y_k}=<\sum_{y_k}(y_k-y_k^{*})^2P(y_k\,|\,x_k)\,|\,Y_{k-1}>$$

$$=< \sum_{r=0}^{\infty} \sum_{s=0}^{2} d_{2s} A_{rs} \theta_r^{(1)}(x_k) \mid Y_{k-1} >$$

$$= \sum_{s=0}^{2} d_{2s} < \mathbf{A}_{(s),k} \Theta(x_k) \mid Y_{k-1} > \tag{23}$$

with

$$\mathbf{A}_{(s),k} = (0,\ \ \mathbf{a}_{(s),k}),\ \ (s=1,\ 2,\ \cdots),\qquad \mathbf{A}_{(0),k} = (1,\ 0,\ 0,\ \cdots,\ 0),$$

$$\Theta(x_k) = (\theta_0^{(1)}(x_k),\ \theta_1^{(1)}(x_k),\ \theta_2^{(1)}(x_k),\ \cdots,\ \theta_R^{(1)}(x_k))^T, \tag{24}$$

where T denotes the transpose of a matrix. The coefficients d_{1s} and d_{2s} in (22) and (23) are determined in advance by expanding y_k and $(y_k - y_k^*)^2$ in the following orthogonal series forms:

$$y_k = \sum_{i=0}^{1} d_{1i} \theta_i^{(2)}(y_k),\quad (y_k - y_k^*)^2 = \sum_{i=0}^{2} d_{2i} \theta_i^{(2)}(y_k). \tag{25}$$

Furthermore, using (1) and the orthonormal condition of $\theta_i^{(2)}(y_k)$, each expansion coefficient $B_{l\mathbf{m}n}$ defined by Eq.(9) can be obtained trough the similar calculation process to (22) and (23), as follows:

$$B_{l\mathbf{m}n} =< \varphi_l^{(1)}(x_k)\varphi_{\mathbf{m}}^{(2)}(\mathbf{a}_k) \sum_{y_k} \varphi_n^{(3)}(y_k) P(y_k \mid x_k) \mid Y_{k-1} >$$

$$=< \varphi_l^{(1)}(x_k)\varphi_{\mathbf{m}}^{(2)}(\mathbf{a}_k) \sum_{r=0}^{\infty} \sum_{s=0}^{n} d_{ns} A_{rs} \theta_r^{(1)}(x_k) \mid Y_{k-1} >$$

$$= \sum_{s=0}^{n} d_{ns} < \varphi_l^{(1)}(x_k)\varphi_{\mathbf{m}}^{(2)}(\mathbf{a}_k) \mathbf{A}_{(s),k} \Theta(x_k) \mid Y_{k-1} >, \tag{26}$$

$(\varphi_n^{(3)}(y_k) = \sum_{i=0}^{n} d_{ni} \theta_i^{(2)}(y_k),\ \ d_{ni}$; appropriate coefficients).

In the above, the expansion coefficient $B_{l\mathbf{m}n}$ can be given by the predictions of x_k and $\mathbf{a}_k$.

Finally, by considering (5) and (6), the prediction step to perform the recurrence estimation can be given for an arbitrary polynomial function $g_{L,\mathbf{M}}(x_{k+1}, \mathbf{a}_{k+1})$ with the $(L, \mathbf{M})$ th order, as follows:

$$g_{L,\mathbf{M}}^*(x_{k+1}, \mathbf{a}_{k+1}) \equiv< g_{L,\mathbf{M}}(x_{k+1}, \mathbf{a}_{k+1}) \mid Y_k >$$

$$=< g_{L,\mathbf{M}}(Fx_k + Gu_k, \mathbf{a}_k) \mid Y_k >. \tag{27}$$

The above equation means that the predictions of x_{k+1} and $\mathbf{a}_{k+1}$ at a discrete time k are given in the form of estimates for the polynomial functions of x_k and $\mathbf{a}_k$. Therefore, by combining the estimation algorithm of (19) and (20) with the prediction algorithm of (27), the recurrence estimation of the specific signal can be achieved.

4. APPLICATION TO PSYCHOLOGICAL EVALUATION OF ROAD TRAFFIC NOISE

To find the quantitative relationship between the human noise annoyance and the physical sound level for environmental noises is important from the viewpoint of noise assessment. It has been reported that the noise annoyance based on the human sensitivity can be distinguished each other from 7 annoyance scores in the psychological acoustics [2]. For instance, 1.very calm, 2.calm, 3.mostly calm, 4.little noisy, 5.noisy, 6.fairly noisy, 7.very noisy.

After recording the road traffic noise by use of a sound level meter and a data recorder, by replaying the recorded tape through amplifier and loudspeaker in a laboratory room, 6 subjects (A, B, …, F) with normal hearing ability judged one score among 7 noise annoyance scores (i.e., 1, 2, …, 7) at every 5 [sec.], according to their impressions of the sound at each moment using 7 categories from very calm to very noisy. Two kinds of data (Data 1 and Data 2) were used, namely, the sound level data of road traffic noise with mean values 71.4 [dB] and 80.2 [dB]. The proposed method was applied to an estimation of the time series x_k for sound level of a road traffic noise based on the successive judgments y_k on human annoyance scores.

Figure 1 shows one of the estimated results of the waveform fluctuation of the sound level. In this figure, the horizontal axis shows the discrete time k, of the estimation process, and the vertical axis represents the sound level. For comparison, the estimated result obtained by introducing the linear system:

$$y_k = \alpha_k x_k + \beta_k + \gamma_k v_k , \tag{28}$$

as the relationship between x_k and y_k for the human evaluation, is also shown in this figure. In (28), v_k denotes a white noise process with mean 0 and variance 1. Since α_k, β_k and γ_k are also unknown parameters, the well-known Extended Kalman filter [6] can be applied to estimate simultaneously the specific signal x_k and the parameters α_k, β_k and γ_k, by introducing the dynamic model on the parameters:

$$\alpha_{k+1} = \alpha_k , \ \ \beta_{k+1} = \beta_k , \ \ \gamma_{k+1} = \gamma_k , \tag{29}$$

in addition to the time transition model of x_k shown in (6). There are great discrepancies between the estimates based on the extended Kalman filter and the true values, while the proposed method estimates precisely the waveform of the sound level with rapidly changing fluctuation.

The root mean squared errors of the estimation are shown in Table 1 (for Data 1) and Table 2 (for Data 2) for both cases applying the proposed method and the extended Kalman filter. It is obvious that the proposed method shows more accurate estimations than the results based on the standard dynamic estimation method.

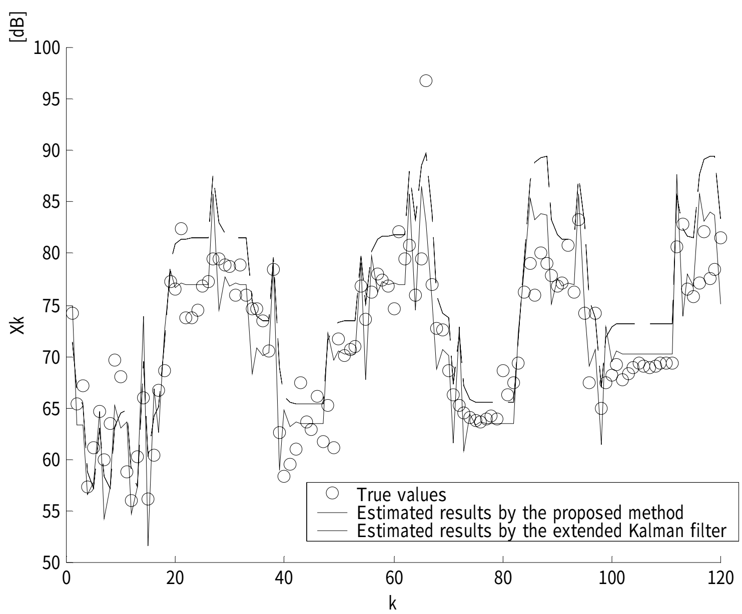

Figure 1. Estimation results of the fluctuation waveform of the sound level based on the successive judgment on human annoyance scores by the subject A (for Data 1).

Table 1. Root mean squared error of the estimation in [dB] (for Data 1).

Subject	A	B	C	D	E	F
Proposed Method	3.94	4.89	4.56	4.28	3.91	3.59
Extended Kalman Filter	5.04	7.53	16.6	7.99	5.46	4.17

Table 2. Root mean squared error of the estimation in [dB] (for Data 2).

Subject	A	B	C	D	E	F
Proposed Method	3.94	4.89	4.56	4.28	3.91	3.59
Extended Kalman Filter	5.04	7.53	16.6	7.99	5.46	4.17

5. CONCLUSIONS

In this paper, based on the observed data with quantized level, a new method has for estimating the specific signal for sound environment systems with unknown structure has been proposed. The proposed estimation method has been realized by introducing a system model of the conditional probability type and regarding the expansion coefficients as unknown parameters to be estimated. The proposed method has been applied to the estimation of an actual road traffic noise, and it has been experimentally verified that better results are obtained compared with a standard estimation technique by introducing a linear system model.

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