Investigation of signal models and methods for evaluating structures of processing telecommunication information exchange systems under acoustic noise conditions

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Abstract. The paper considers models and methods for estimating signals during the transmission of information messages in telecommunication systems of audio exchange. One-dimensional probability distribution functions that can be used to isolate useful signals, and acoustic noise interference are presented. An approach to the estimation of the correlation and spectral functions of the parameters of acoustic signals is proposed, based on the parametric representation of acoustic signals and the components of the noise components. The paper suggests an approach to improving the efficiency of interference cancellation and highlighting the necessary information when processing signals from telecommunications systems. In this case, the suppression of acoustic noise is based on the methods of adaptive filtering and adaptive compensation. The work also describes the models of echo signals and the structure of subscriber devices in operational command telecommunications systems.

1. Introduction

The tasks of signal processing in audio exchange systems are determined by the needs of information extraction, interference suppression, increasing the stability of communication systems and echo compensation.

In the research of issues of the processing of signals, it is possible to set tasks: estimating and approximating one-dimensional distribution functions and correlation functions from limited data sets and, on this basis, forming a basis for a priori information and allocating the intervals of stationarity of the observed signals; smoothing and local approximation of the observed signals and, on this basis, segmentation of non-stationary signals; detection and evaluation of harmonic signals, signals with a discrete spectrum on the background of acoustic noise with continuous distribution and, on this basis, diagnostics of objects; spectral analysis of the observed signals and, on this basis, the resolution of radiation sources and the selection of the speech signal and interference; formation of an echo-signal model and estimation of its parameters; identification of non-stationary signals and creation of non-stationary models for observable data; adaptive compensation for acoustic noise and echoes using multi-channel and multi-speed processing.

2. Single-dimensional functions of distribution

One-dimensional distribution functions are a fairly simple means of distinguishing signals that can be used to distinguish between speech and noise. Approximation of the speech distribution functions
discussed in the works can be formulated as an optimization problem with constraints. Namely, the problem of minimizing the square of the norm:

$$
\| f(\theta) - \hat{f} \|^2 \rightarrow \min, \quad P(x, \theta) \geq 0, \quad \int_{a_{k-1}}^{a_k} P(x, \theta) dx = 1. \quad (1)
$$

Here $\hat{f}$ – vector of values of the histogram characterizing the distribution of samples of the observed signal. The components of vector $f(\theta)$ are, respectively, the probabilities with which the values of the observed signal fall within the intervals of histogram $[a_{k-1}, a_k], \ k = 1, \ldots, n$.

That is, $f_k(\theta) = \int_{a_{k-1}}^{a_k} P(x, \theta) dx$. In this case, $P(x, \theta)$ is an approximation of the sought probability density function, $\theta$ – vector of parameters for minimization. For the purposes of regularization, additional constraints can be imposed on parameter vector $\theta$.

The statistical characteristics of the parameter vector representing the solution of problem (1) depend substantially on the volume of the samples used. The establishment of this dependence is a necessary basis for the reliability of the obtained approximation results.

3. Methods of parametric representation of random processes

Another approach to the estimation of signal models is based on the parametric representation of random processes. This approach is widely used in the analysis of time series and assumes the existence of some discrete model described by the corresponding difference equation. In problems of optimal filtering, processes are often modeled with the help of dynamic systems excited by random signals with known characteristics [1]. In the case of acoustic signals, this approach is also fully justified, especially if one takes into account the completely deterministic mechanism of their formation. In this case, the input effects can be attributed to regular signals with unknown, possibly changing parameters, rather than to random processes. Acoustic and mechanical resonances of natural and artificial objects under the influence of wind cause sounds at the corresponding resonance frequencies, the intensity of which depends on the speed and direction of the wind. The characteristics of the wind, which is quite regular at small intervals, in general, are subject to considerable changes. All this in terms of noise control and allocation of useful signals leads to the task of identifying parameters, both the model itself and the input effects.

Models of signals and interference are an integral part of many adaptive systems. Naturally, they can be applied to the processing of acoustic signals, which, as a rule, is associated with the task of suppressing interference and separating the necessary information from the observed data.

In a broad sense, interference cancellation can be based on both adaptive filtering methods and compensation methods [2, 3]. In the first case, interference is eliminated by appropriately designed blocking filters, and in the second - by subtracting its estimate from the observed signal. However, in the future, for the sake of simplicity, suppression will be more often considered in the narrow sense - as a filtering of interference. Discrete systems, described by difference equations, or the form of autoregression - the moving, are used as signal models:

$$
x_k = a_1 x_{k-1} + a_2 x_{k-2} + \cdots + a_p x_{k-p} + u_k - b_1 u_{k-1} - b_2 u_{k-2} - \cdots - b_q u_{k-q}, \quad (2)
$$

or a type of system state variables:

$$
y(k + 1) = Ay(k) + Bu(k), \quad x(k) = Cy(k) + Du(k), \quad (3)
$$

where $y \in R^n$ – state vector, $u \in R^m$ – vector of input influences and $x \in R^h$ – vector of outputs. Accordingly, matrices $A$, $B$, $C$ and $D$ have the following dimensions: $n \times n$, $n \times m$, $h \times n$ and $h \times m$. In this case, the estimation of the spectra is reduced to estimating the parameters of model (2) or (3).

Equation (2) is, as its name implies, a combination of two models - an autoregressive model, if all the coefficients $b_k = 0$, and the moving average model, if $a_k = 0$.

For system (3), the images of the vector of state variables and the output vector of the model are
written in the form:

\[ Y(z) = (zI - A)^{-1} BU(z), \quad X(z) = C(zI - A)^{-1} B + D U(z). \]  

(4)

Accordingly, the spectrum of the outputs are described by the expression:

\[ X(\omega) = C \left( e^{j\omega I} - A \right)^{-1} B + D \left[ U(\omega) \right]. \]  

(5)

Usually, the model described by expressions (3) - (5) depends only on the state of the system, while \( x(k) = Cy(k) \) and matrix \( D = 0 \).

The task of identifying model (3) can consist not only in evaluating matrices \( A, B \) and \( C \), but also in evaluating the state of the system. In this case, a technique based on replacing the model in state variables with an equivalent autoregression model is sometimes used.

The task of identification in many cases is the task of minimizing some loss functional characterizing the deviation of the result of approximation \( \hat{x}(k) \) from observed data \( \bar{x}(k) \), \( k = 1, \ldots, N \):

\[ \rho(\hat{x}, \bar{x}) \rightarrow \min. \]

Here \( \hat{x} = (\hat{x}(1) \ \hat{x}(2) \ \ldots \ \hat{x}(N))^T \) and \( \bar{x} = (\bar{x}(1) \ \bar{x}(2) \ \ldots \ \bar{x}(N))^T \) - vectors of the results of approximation and observable data, respectively. Equation (2) or (3) acts as a limitation of the problem. Other constraints are also possible, due, for example, to the stability conditions of the model.

This loss functional in the solution of ill-posed problems is supplemented by regularizing functional \( \Omega(\hat{x}(t)) \), which can have a set of functions of both discrete and continuous time for its definition. In this case, the identification problem takes the form:

\[ \rho(\hat{x}, \bar{x}) + \alpha \Omega(\hat{x}(t)) \rightarrow \min. \]

In many cases, the loss functional uses the norm characterizing the distance between the observed data and the values of the function obtained as a result of identification: \( \rho(\hat{x}, \bar{x}) = \frac{1}{2}\|\hat{x} - \bar{x}\|^2 \).

In the case of a Hilbert space, the norm is represented by a scalar product, and loss functional \( \rho(\hat{x}, \bar{x}) = \frac{1}{2}\langle \hat{x} - \bar{x}, \hat{x} - \bar{x} \rangle \) is a quadratic function of estimating the signal from the observed data.

If the constraints also have the form of quadratic or linear functions, then the problem of quadratic programming takes place.

Vector \( \hat{x} \) can be formed by samples of continuous time function \( \hat{x}(t) \) represented as a linear or nonlinear regression. Namely, in the form of function \( \hat{x}(t) = g(t, a) \) that depends on optimization parameter vector \( a \). In the case of linear regression, this function takes form \( \hat{x}(t) = \varphi^T(t) a \), where \( \varphi(t) = (\varphi_1(t) \ \varphi_2(t) \ \ldots \ \varphi_n(t))^T \) is a vector in a system of linearly independent functions \( \varphi_k(t), k = 1, \ldots, n \).

In this case, vector \( \hat{x} \) can be written in form \( \hat{x} = \Phi a \), where the rows of matrix \( \Phi \) are the values of the transposed vector functions.

Then the problem of minimizing the loss function in the case of nonlinear regression can be written in the form:

\[ \frac{1}{2}\|g(a) - \bar{x}\|^2 \rightarrow \min, \]  

(6)

and in the case of linear regression, in the form:

\[ \frac{1}{2}\|\Phi a - \bar{x}\|^2 \rightarrow \min. \]  

(7)

As is known, the mathematical expectation of function (6) or (7) reaches its lowest value if vector \( g(a) \) or \( \Phi a \) coincides with the conditional mathematical expectation of vector \( x \), \( E\{x|\bar{x}\} \).
considered as a function of observable data $\bar{x}$. In this case, the loss value coincides with the conditional variance, if only coefficient $1/2$ is discarded.

The vector of regression coefficients $\hat{a}$ obtained as a result of minimizing the loss function determines optimal solution $\hat{x}(t) = \phi^T(t \hat{a})$ as a function of continuous time. This allows one, if necessary, to impose additional constraints on its behavior between data samples, using, for example, a regularizing functional.

The achievable accuracy of the approximation of the observed data by the regression function depends to a large extent on the size of its domain. With an increase in the size of the area within which the observed data do not tend to zero, the accuracy decreases. Let us eliminate this disadvantage by using the local approximation method [4]. Approximation of observable data in this case is provided by a sequence of regression functions, each of which is given on its finite interval. At the same time, this allows approximating non-stationary signals and systems.

The question of conjugation of individual regression functions can be solved if the constraints presented in the minimization problem are supplemented by the conditions for matching the values of these functions and, possibly, the values of their derivatives at the conjugation nodes.

Let us put the problem of determining the parameters in observed signal $x(t)$, which is the additive sum of estimated signal $s(t)$ and acoustic noise $\gamma(t)$, which is also considered as a complex function. In the discrete form, this signal has the form:

$$x(k) = s(k) + \eta(k) = \sum_{n=1}^{p} a_n e^{j(n f_0 k + \phi_n)} + \eta(k).$$

(8)

Here $f_0$ - sampling frequency.

The problem of determining the parameters of function (8) can also be solved by the method of maximum likelihood, the application of which is complicated by the insufficient reliability of a priori information on the interference distributions. The maximum likelihood method, as is well known, in the case of independent identically distributed Gaussian quantities is equivalent to the method of least squares. In this case, the parameters of the function (8) can, in principle, be found by methods of non-linear programming. Namely, in the case of function (8), by solving the minimization problem:

$$\{\hat{\omega}, \hat{a}, \hat{\phi}\} = \arg\min_{\{\omega, a, \phi\}} \|v - x\|^2.$$

If one introduces the vectors of samples of the signal to be extracted $s = (s(1) \ s(2) \ \cdots \ s(N))^T$ and observed signal $x = (x(1) \ x(2) \ \cdots \ x(N))^T$, vectors $a = (a_1, \ldots, a_p)^T$ and $\phi = (\phi_1, \ldots, \phi_p)^T$, then the norm can be written in the form:

$$\|s - x\|^2 = \langle s - x, s - x \rangle = \sum_{k=1}^{N} \sum_{n=1}^{p} a_n e^{j(n f_0 k + \phi_n)} - x(k)^2.$$
\[
\hat{a} = \arg \sup_a P( y^a_n | a ) .
\]

The maximum likelihood method can be used under certain conditions if the observed data are a sequence of independent random variables with probability density \( p( y_k | a ) \). In this case, the likelihood function has the form of \( P( y^a_n | a ) = \prod_{k=1}^{n} p( y_k | a ) \).

In connection with the above-mentioned methods of parametric optimization and local approximation, it should be noted that they are practically equivalent in their content to projection methods for solving operator equations, projection and interpolation methods of analysis and calculation of systems.

4. Models of echo-signals and structure of subscriber devices in operational command telecommunication systems of communication

In free space, echo signals are formed as a result of reflections caused by the peculiarities of the terrain, the location of buildings and large-sized objects. Significant areas of the territory lead to large delays in the propagation of echoes and a decrease in the intelligibility of speech. In addition, in an acoustic field with a multitude of different echo channels, zones of silence often arise, which, in particular, must be taken into account when designing warning systems. The impulse functions in the echo propagation channels can be taken as some constant transmission coefficients.

With this in mind, the multiple reflection model takes the form:

\[
y(t) = \sum_{k=1}^{r} a_k u(t - \tau_k) = \sum_{k=1}^{r} a_k u(t - D_k T) .
\]

The task here is to determine attenuation \( a_k \) and lag parameters \( \tau_k = D_k T \) for the \( r \) echo channels. By conditions, signal \( u(t) \) whose reflections form echo signals \( y(t) \) is known and non-stationary. This allows us to apply the correlation analysis in the estimation of parameters \( a_k \) and \( D_k \). In this case, the signal processing algorithm for compensating echo reflections \( y(t-D) \) and for suppressing acoustic noise interference \( y(t) \) can be described as follows:

- the microphone input receives signal \( x(t) = u_0(t) + y(t-D) + \gamma(t) \);
- in the block of calculation of long-term parameters, \( D_k \) and \( a_k \) are calculated by the method of correlation-extreme estimation, in the form of \( R_{u_0,x} = \frac{1}{N+1} \sum_{n=0}^{N} x(n-D)u_0(n) , \hat{a_k} = \frac{R_{u_0,x}}{R_{u_0,u_0}(0)} \), if \( \hat{a_k} \geq \beta \), then \( D = \hat{D}_k \);
- the reference signal for the adaptive filter of the L-th order is computed as \( \hat{y}_k(n) = \hat{a}_k u_0(n-\hat{D}_k+L/2) \);
- output of adder \( x(n) = u_0(n) + e(n) + \gamma(n) \), \( e(n) = y(t-D) - \hat{y}(t-D) \);
- at the output of the noise canceling device:
  \[
x(n) = u_0(n) + e(n) + B \gamma(n) , \quad B < 0,01 , \quad e(n) < 0,01 , \quad \text{then} \quad x(n) = u_0(n).
\]

Thus, the structure of the subscriber unit in accordance with the processing algorithm presented above is shown in Figure 1.

In accordance with Figure 1 in the subscriber unit there are a block for calculating the long-term parameters of echo \( a_k \) and \( D_k \), the adaptive filter reference signal generating unit, an echo cancellation unit including an adaptive filter and an adder, and a noise canceling device implementing an adaptive noise cancellation algorithm with a formant band distribution rejection [4].

Unlike the open territory, the echo signal in enclosed spaces is more correctly considered as an integral sum of components continuously distributed in terms of the delay value. A fairly good
approximation to reality may be the use of an echo model. Impulse functions \( h_k(t) \) that enter these expressions imitate, at the same time, the continuous distribution of delays within relatively small neighborhoods \( \{ \tau_k - \varepsilon, \tau_k + \varepsilon \} , k = 0,1,\ldots, r \), allocated to the main echo channels.

5. Conclusion
The problem of signal processing in telecommunication systems of voice transmission is caused by the lack of reliable a priori information about the characteristics of the observed signals. The problems of estimating the parameters of models are solved by various methods, depending on the restrictions on the statistical characteristics of the observed signals. The most promising methods for these conditions can be considered; this is the method of minimizing the loss function, the maximum likelihood method, and the correlation function correlation method [6, 7, 8].

Modeling of external noise of echoes can be considered as a means of overcoming a priori uncertainty, based on the extraction of relevant information from the observation results [9, 10].

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