

## TECHNIQUES OF RANDOM SIGNAL RECOGNITION FOR SOLUTION TO APPLIED PROBLEMS

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**Abstract:** Solutions to non-traditional problems of signal recognition are considered. Special treatment is given to the case when defined in the probabilistic sense signals to recognize are mixed with unknown signals. Methods for selection and recognition of a defined random signal are proposed for the cases when signal's description is done by various probabilistic models. Real-life peculiarities of application of methods for selection and recognition of a defined random signal in the field of radiolocation, automated radiomonitoring, medical diagnostics and speaker identification are given.

**Key words:** random signal, recognition, decision rule, hypothesis, radiolocation, radiomonitoring, medical diagnostics, speaker identification.

### 1. Introduction

When we solve applied problems of recognition in the field of radiolocation, radiomonitoring, technical and medical diagnostics and at speaker identification, information about objects to recognize is represented in the form of a random signal taken from the output of a corresponding physical sensor of the signal. There arises the necessity to process this information to make a decision on whether the given object or state belongs to one of the predefined classes after considering random signals representing them. When synthesizing statistical recognizers, we need to choose an adequate mathematical model of a signal being recognized, obtain signal's probabilistic characteristics and provide optimality criterion. In specific applied problems different types of random signal to recognize require to use various probabilistic models in order to describe the signal. A priori uncertainty (i.e. absence of a priori knowledge related to the signal probabilistic characteristics) is commonly overcome by using learning samples of signals being recognized. As a result we adopt the recognizer to the conditions of a particular applied problem [1-3]. However, in practice unknown signals (i.e. signals that we cannot get any learning sample for them) are also given for recognition along with statistically defined signals. In this case classical recognition methods cannot be used. Therefore there is a necessity for development of non-traditional signal selectors and recognizers which take into account the presence of an unknown signal class. There

was given no consideration to such recognition problems in known treatises on pattern recognition. Only in [2] one can find spectral methods for the defined random signal recognition in presence of the unknown signal class for the case when signals are described by the probabilistic model in the form of an orthogonal decomposition of a random signal.

In the present work we consider some non-traditional methods for selection and recognition of a statistically defined random signal subject to the presence of an unknown signal class for the case of describing the signal by different probabilistic models and in particular in the form of autoregressive processes and mixtures of normal distributions. There are given results of solutions to some applied problems of recognition by using considered methods for selection and recognition of defined random signals. Research of recognizers is done by statistical modelling based on samples of signals typical for the problems of radiolocation, automated radiomonitoring, medical diagnostics and speaker identification [4-10].

### 2. Statement of the problem of signal recognition

We assume that signal being recognized is represented by a finite dimensional random vector  $\mathbf{x}$  of equidistantly spaced samples of the signal. Decisions on signals' belonging are made on their realizations. We put forward  $(M + 1)$  hypotheses that can be formulated with reference to the observed signals, namely,  $H^i, i = \overline{1, M}$  are for statistically defined signals,  $H^0$  is for signals gathered into the  $(M + 1)$ -th class and possessing unknown probabilistic characteristics. Probability densities  $W(\mathbf{x} / \mathbf{\alpha}^i), i = \overline{1, M}$  of the statistically defined signals are defined accurate within random vector parameters  $\mathbf{\alpha}^i, i = \overline{1, M}$  and the probability density is unknown for the  $(M + 1)$ -th class. A priori probabilities of hypotheses  $P(H^i) = P_i$  are also given and  $\sum_{i=0}^M P_i = 1$

It is assumed that learning samples for  $M$  defined signals  $\{\mathbf{x}_r^i, r = \overline{1, n_i}; i = \overline{1, M}\}$  are given and a

learning sample for the  $(M + 1)$ -th class of unknown signals ( $i = 0$ ) is either absent or unrepresentative. Such initial data for signal recognition can be described with the notion “increased a priori uncertainty” [5].

Now we proceed with the form analysis of the signal recognition quality factor characterized by the average risk [2, 3]:

$$R = \sum_{l=1}^M \sum_{i=1}^M c_{li} P_i P(G^l / i) + \sum_{i=1}^M c_{0i} P_i P(G^0 / i) + P_0 \sum_{l=1}^M c_{l0} P(G^l / 0), \quad (1)$$

where  $c_{li}$  is a loss function;  $P(G^l / i)$  is the probability of the error that arises when we make a decision for the  $l$ -th signal, when the  $i$ -th signal is present.

A non-randomized decision rule of recognition does the sample space partitioning into  $M$  non-overlapping domains. Allowing for that, the first term in (1) is the component of the average risk caused by a wrong recognition of a defined signal as the other one. The second term is the component of the average risk due to reference of a defined signal to the  $(M + 1)$ -th class of unknown signals. The third term is the component of the average risk due to reference of an unknown signal from the  $(M + 1)$ -th class to one of  $M$  defined signals.

According to the available information it is possible to find within the stated problem of recognition, estimates of the first two components in (1). It does not seem possible to estimate the third component. With the aim to take into account the third term we offer to introduce a scalar parameter that is equal to the volume of the rejection region

$$G = \bigcup_{i=1}^M G^i \text{ for the hypothesis } H^0 \text{ on the presence of an}$$

$(M + 1)$ -th signal. This region has meaning of the proper region of  $M$  defined signals. From the intensional point of view, the recognition problem we have under consideration consists in making a decision on presence of one of  $M$  defined signals and referencing unknown signals to the  $(M + 1)$ -th class. In connection with the above, this problem of recognition can be treated as the problem of selection and recognition of defined random signals.

### 3. Decision rules for selection and recognition of defined signals

Solution to the formulated above non-traditional problem of signal selection and recognition gives the following decision rule [2]:

– accept the hypothesis  $H^0$  on the presence of the  $(M + 1)$ -th class of unknown signals if

$$H^0 : \max_{l=1, M} \{ P_l W(\mathbf{x} / \mathbf{\alpha}^l) \} < \lambda; \quad (2a)$$

– accept the hypothesis  $H^i$  on the presence of the  $i$ -th defined signal if

$$H^i : P_i W(\mathbf{x} / \mathbf{\alpha}^i) \geq \lambda, \quad (2b)$$

$$P_i W(\mathbf{x} / \mathbf{\alpha}^i) \geq P_l W(\mathbf{x} / \mathbf{\alpha}^l), l = \overline{1, M}, l \neq i. \quad (2c)$$

Parameters  $\mathbf{\alpha}^l, l = \overline{1, M}$  are estimated on learning samples for defined signals. The value for the threshold  $\lambda$  is chosen to provide the given probability of correct recognition of a defined signal.

Note that any information about probability distribution density of a signal from the  $(M + 1)$ -th class as well as its learning sample was not used at deriving this decision rule. Statement and solution to the considered problem is formalization of the requirements for the necessity to recognize  $M$  defined signals and reference an unknown signal to the  $(M + 1)$ -th class since information about it is insufficient for its recognition. Geometrical sense of the decision rule is explained in Fig 1, where  $\hat{G}_p$  is the estimate of the vector of mathematical expectation found for the  $p$ -th signal;  $y_p$  is the proper region of the  $p$ -th signal;  $\rho_{pz}$  is the Euclidean distance measured from the observed realization of a signal to the centre of the  $p$ -th signal proper region;  $\rho_{Gp}$  is the value that defines the volume of the  $p$ -th signal proper area.

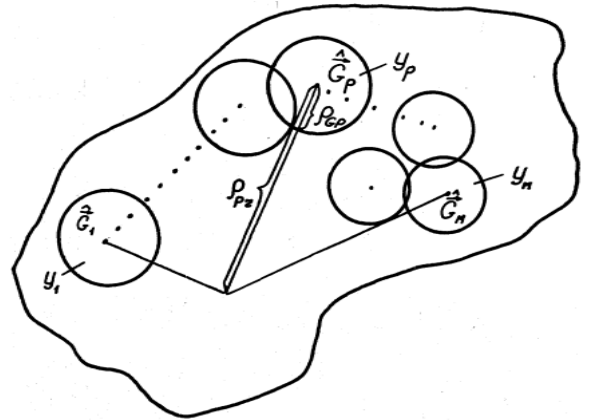


Fig. 1. Geometrical sense of the decision rule (2).

The decision rule (2) gives the general solution to the stated problem of selection and recognition of defined signals at presence of unknown signals. Specificities of decision rules for recognition of a signal described by the probability model in the form of orthogonal decompositions are presented in [2]. This model gives us a spectral representation of a signal. In this case in the mentioned decision rule (2) we substitute the signal, given by the vector  $\mathbf{x}$  for the vector  $\mathbf{r} = \mathbf{x}^T \mathbf{\Phi}$  of components of that signal decomposition over some basis, where  $\mathbf{\Phi}$  is a matrix of basis vectors.

Now we are going to consider peculiarities of the decision rule of recognition (2) which was featured for the case of describing a signal to recognize by some other probabilistic models, namely, autoregressive processes or mixtures of probability distributions.

In particular, if one describes signal by the probabilistic model in the form of Gaussian autoregressive process the decision rule (2) takes the form [4, 6]:

- accept the hypothesis on the presence of the  $i$ -th signal if

$$H^i : K_i(\mathbf{x}) < \Lambda_i, \quad (3a)$$

$$K_i(\mathbf{x}) - K_i(\mathbf{x}^i) + \ln \frac{(2\pi\sigma_i)^{p_i-L}}{(2\pi\sigma_i)^{p_i-L}} \geq \ln \frac{P_i}{P_i}, \quad (3b)$$

- accept the hypothesis on the presence of an unknown signal if

$$H^{M+1} : K_l(\mathbf{x}) > \Lambda_l, \quad l = \overline{1, M}, \quad (3c)$$

$$K_l(\mathbf{x}) = (2\pi\sigma_l^2)^{-1} \sum_{k=p_l+1}^L [x_k - \mu_l - \sum_{j=1}^{p_l} a_j^l (x_{k-j} - \mu_l)]^2$$

is the expression defining the standardized prediction error in the autoregressive model;  $p_l, a_j^l$  are the order and parameters of the autoregressive model for the  $l$ -th signal;  $\Lambda_l = \ln[(2\pi)^{\frac{L}{2}} \sigma_l^{L-p_l} \lambda_l / P_l]$  are some threshold values chosen so as to provide the given probabilities of  $M$  defined signals correct recognition;  $x_k$  is the value of the  $k$ -th component of the vector  $\mathbf{x}$ ;  $L$  is the dimensionality of a random vector  $\mathbf{x}$ ;  $\mu_l, \sigma_l^2$  are respectively the mean and variance of the  $l$ -th signal.

When using such the probabilistic model as a mixture of probability distributions the decision rule of recognition (2) takes the following form [4]:

- accept the hypothesis on the presence of the  $i$ -th signal if

$$\max_{l=1, M} \{P_l \sum_{q=1}^Q g_q W_q(\mathbf{x} / \mathbf{\alpha}^l)\} \geq \lambda, \quad (4a)$$

$$P_i \sum_{q=1}^Q g_q W_q(\mathbf{x} / \mathbf{\alpha}^i) \geq P_l \sum_{q=1}^Q g_q W_q(\mathbf{x} / \mathbf{\alpha}^l), \quad (4b)$$

$$l = \overline{1, M}, \quad l \neq i$$

- accept the hypothesis on the presence of an unknown signal from the  $(M+1)$ -th class if

$$\max_{l=1, M} \{P_l \sum_{q=1}^Q g_q W_q(\mathbf{x} / \mathbf{\alpha}^l)\} < \lambda, \quad (4c)$$

where  $Q$  is the number of components in the mixture and  $g_q$  are parameters of the mixture.

In the proposed decision rules we assume that distribution parameters  $\mathbf{\alpha}^i$  are either known or there should be used their estimates found on defined signal classified learning samples.

However in some applied problems after the learning stage, signal likelihood functions may be defined accurately within unknown parameters  $\hat{\beta}^i$ , which are subject to estimate on the observed signal realization directly during the recognition process. In such a situation one can use a decision rule of signal recognition obtained within the adaptive Bayesian approach:

- accept the hypothesis on the presence of the  $i$ -th defined signal if [10]

$$\max_{i=1, M} \max_{\beta^i} \{P_i W_i(\mathbf{x} / \mathbf{\alpha}^i, \hat{\beta}^i)\} \geq \lambda, \quad (5a)$$

$$\max_{\beta^i} \{P_i W_i(\mathbf{x} / \mathbf{\alpha}^i, \hat{\beta}^i)\} \geq \max_{\beta^l} \{P_l W_l(\mathbf{x} / \mathbf{\alpha}^l, \hat{\beta}^l)\}, \quad (5b)$$

$$l = \overline{1, M}, \quad l \neq i;$$

- accept the hypothesis on the presence of an unknown signal from the  $(M+1)$ -th class if

$$\max_{i=1, M} \max_{\beta^i} \{P_i W_i(\mathbf{x} / \mathbf{\alpha}^i, \hat{\beta}^i)\} < \lambda. \quad (5c)$$

In case when the linear prediction model is used, the following decision rules can be obtained based on the decision rule (5) [10]

$$i = \min_{j=1, M} \left( \ln \sum_{k=0}^{n-1} \frac{x_k}{x_k^{(j)}} + \frac{1}{n} \sum_{k=0}^{n-1} \ln x_k^{(j)} \right), \quad (6)$$

$$i = \min_{j=1, M} \sum_{k=0}^{n-1} (\sqrt{x_k} - \hat{\beta}^{(j)} \sqrt{x_k^{(j)}})^2, \quad (7)$$

where  $x_k$  is the value of the  $k$ -th component of the feature vector  $\mathbf{x}$  of a signal being observed;  $x_k^{(j)}$  is the value of the  $k$ -th component of the feature vector  $\mathbf{x}^{(j)}$  of the  $j$ -th defined signal;  $\hat{\beta}^{(j)} = \sum_{k=0}^{n-1} \sqrt{x_k x_k^{(j)}} \cdot (\sum_{k=0}^{n-1} x_k^{(j)})^{-1}$ .

While getting these decision rules we supposed that the features were statistically independent and their distributions allowed approximations by the  $\chi_2^2$  distribution (rule (6)) or by the normal distribution with equal variances (rule (7)).

#### 4. Results of research into methods of signal selection and recognition

Considered above methods of statistically defined signal selection and recognition have been used to solve some applied problems of object recognition with respect to representing it random signal acting in the field of radiolocation, radiomonitoring, medical diagnostics and speaker identification [4-10]. Research

has been done by statistical modelling based on signal samples typical for a particular applied problem.

The decision rule (2) based on the probabilistic model in the form of random signal orthogonal decompositions was used while solving the problem of air object radar recognition with respect to samples of remote portraits [5]. The research was performed with respect to samples of remote portraits corresponding to objects of three types: large, medium and small sized, obtained by modelling for the case when probing signals were in the form of a coherent bundle of wideband chirp pulses (Fig. 2). In the result of our research the estimate for the average probability of object correct recognition was found; it is equal to 0.92.

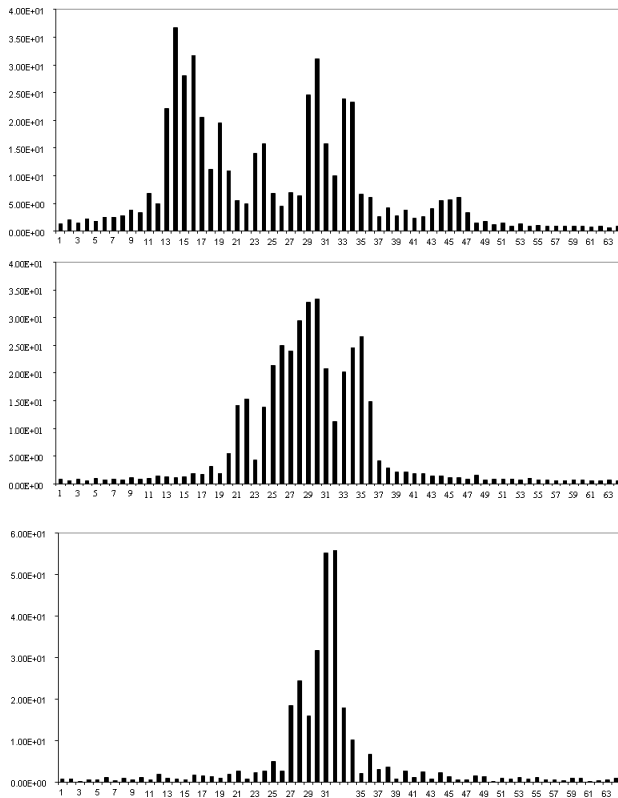


Fig. 2. Representation of objects as remote portraits.

There were also considered peculiarities of object type radar recognition when one uses the vector autoregressive model to provide mathematical description of signals in a bundle of remote portraits [7].

Investigations into the radar recognition of meteorological object with respect to intensity fluctuations of incoherent pulse radar reflected signals were performed by using the decision rule based on the model in the form of an autoregressive process [8]. Unknown parameters of the model for intensity fluctuations of reflected signals were obtained with the aid of classified samples of reflected signals for the four types of clouds: cirrus, continuous gray, alto-cumulus, cumulus powerful clouds. Obtained estimates for the model parameters are shown in Fig. 3.

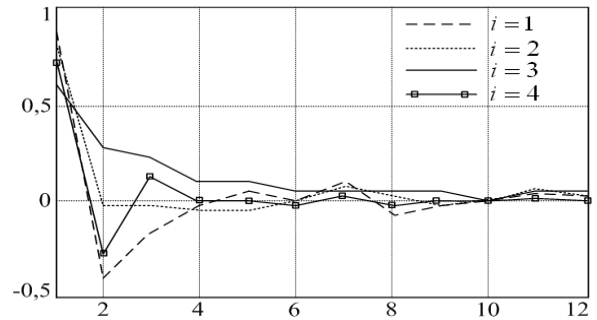


Fig. 3. Estimates of parameters of the model for intensity fluctuations of reflected signals.

In the issue of our investigations, the estimate of the average probability of cloud correct recognition was found with respect to control samples of real signals that were reflected off different types of clouds. The probability lies in the range 0.8–0.9.

While investigating into the radio transmission type recognition problem that appears in the area of automated radiomonitoring, the decision rule (3) was used [4]. The research was carried out with the aid of signal samples corresponded to radio emissions with different types of modulation that are typical for the problems of automated radiomonitoring. Their averaged power spectra are shown in Fig 4. The estimate for the average probability of correct recognition, being equal to 0.95, was obtained.

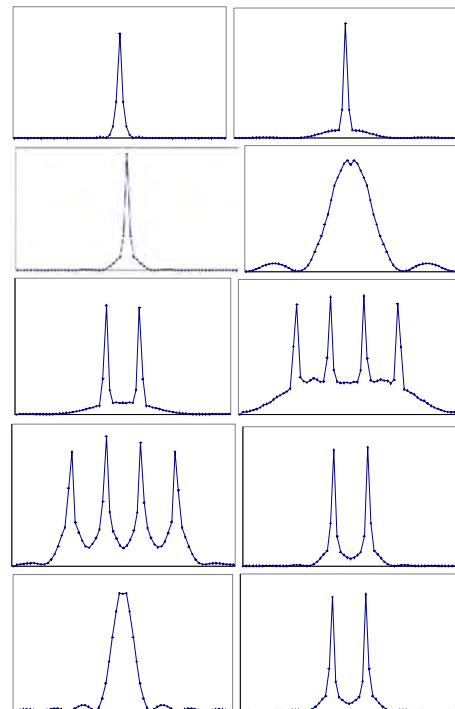


Fig. 4. Averaged power spectra of signals to recognize.

The decision rule (4) was used while investigating into another problem of automated radiomonitoring, namely, the problem of recognition of radio signal modulation type [4]. The investigations were carried out by using samples of radio signals possessing different

types of modulations that are common for automated radio monitoring (2-ASK, 2-FSK, 2-PSK, 4-PSK, 16-QAM). The estimate for the average probability of correct recognition, being equal to 0.9, was obtained.

While investigating into the problem of automated recognition of sleep stages with the aid of electroencephalogram (EEG) the decision rule (3) was used. The research was conducted by using samples of EEG realizations for six stages of sleep [9]. Parameters of the decision rule (3) were found with respect to classified EEG learning samples. Control samples were used while researching into real-life peculiarities of solution to the problem of automated recognition of the sleep stages with EEG. As the result of recognition of EEG samples corresponding to different stages of sleep, diagrams of sleep stages change were obtained. Such a diagram is shown in Fig. 5. The estimate for the minimal value of the average probability of the sleep stage false recognition, being equal to  $P_{err} = 0.15$ , was obtained.

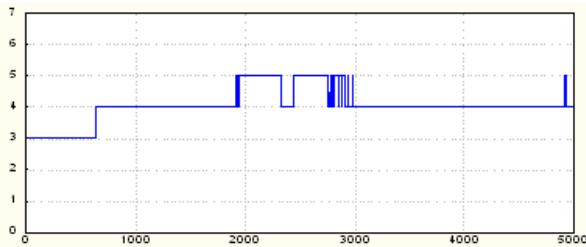


Fig. 5. A diagram of sleep stages change.

The problem of subscriber identification (recognition) with respect to human's voice was investigated with the use of decision rules (6) and (7) [10]. It was supposed that the speech signal was represented in the digital form and had sampling frequency 8 KHz. Next, the signal was processed by a PARCOR-based vocoder of the 10-th order. The length of the interval (segment) to estimate parameters of the vector was taken equal to 30 ms. To classify speech signal segments into voiced and unvoiced ones we used autocorrelation method. As the features we used coefficients of the Fourier transform of the autocorrelation function of the transformed speech signal as well as the linear prediction residual signal that were passed through different discrete-time windows (triangular, Hanning, Hamming). Fig. 6 plots spectrograms (voiceprints) of the initial speech signals (Fig. 6a, 6c) and the linear prediction residual signals (Fig. 6b, 6d) for different subscribers. In the issue of our research the following estimates for the average probability of speaker correct recognition was obtained: 0.97 for the case when there were no frequency distortions in the transmission channel and 0.94 when the distortions were present in the transmission channel.

## 5. Conclusion

Solutions to a non-traditional random signal recognition problem have been considered, namely, the problem when unknown signals are presented for recognition along with signals defined in the probabilistic sense.

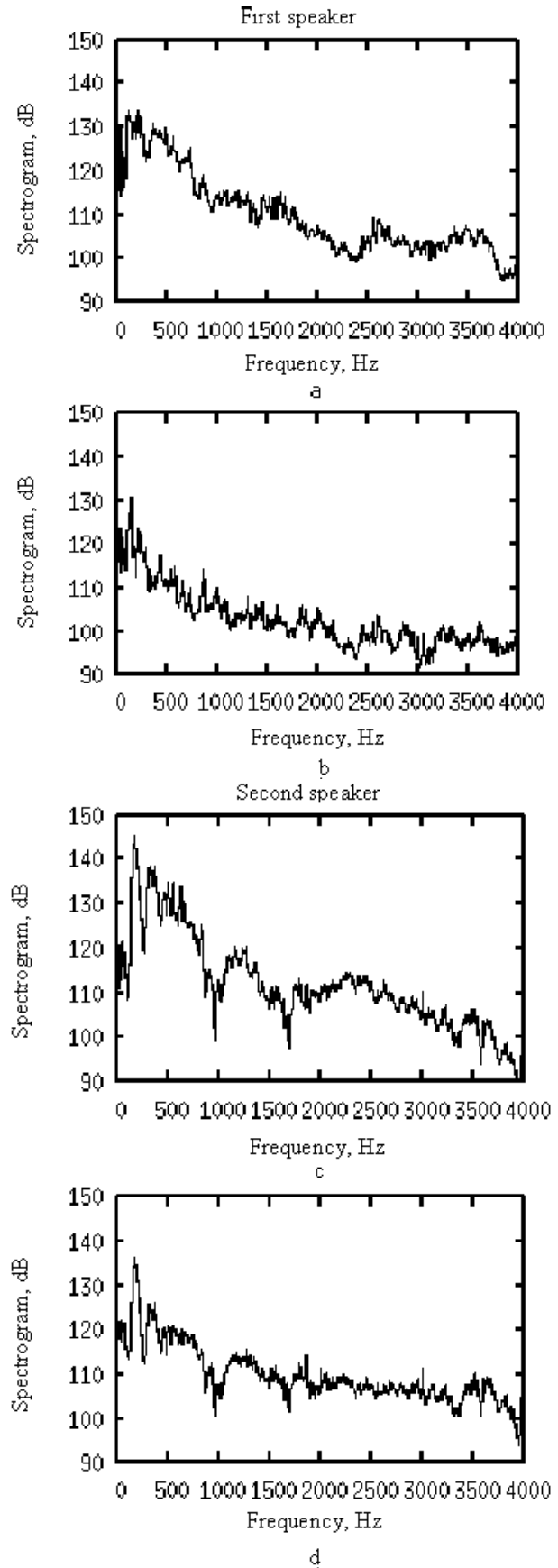


Fig. 6. Voice prints of two speakers (a, b) along with spectrograms of linear prediction residual signals (c, d).

Methods for selection and recognition of a defined random signal subject to the presence of the unknown signal class have been considered. Special consideration has been given to the cases when signal description is done by using such probabilistic models as orthogonal decompositions, autoregressive process and mixtures of probability distributions.

Practical significance of the proposed methods for signal selection and recognition in the field of radiolocation, automated radiomonitoring, medical diagnostics and speaker identification has been proved by given results of the conducted research.

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## МЕТОДИ РОЗПІЗНАВАННЯ ВИПАДКОВИХ СИГНАЛІВ ДЛЯ ВИРІШЕННЯ ПРИКЛАДНИХ ЗАДАЧ

Валерій Безрук, Анатолій Омельченко,  
Олексій Федоров

Розглянуто вирішення нетрадиційних задач розпізнавання сигналів, коли на розпізнавання подаються невідомі сигнали наряду з сигналами, заданими у ймовірнісному сенсі. Запропоновано методи селекції і розпізнавання заданих випадкових сигналів під час їх описування різними ймовірнісними моделями. Наведено практичні особливості застосування методів селекції і розпізнавання заданих сигналів у галузях радіолокації, радіомоніторингу, медичної діагностики та ідентифікації дикторів.



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