

INVARIANT SIGNAL RECOGNITION IN NOISE ENVIROMENT

Riad Taha Al-Kasasbeh

Faculty of Engineering Technology, Al-Balqa Applied University, Amman, Jordan

Keywords: signal/noise, speech recognition, invariant signal recognition.

Abstract: Recognition of signals is considered at the presence of noise. The problem is actual for the speech signals recognition, acoustic diagnostics of mechanisms. The model of recognized signal contains a priori unknown parameter - the relation a signal / noise. For considered model the approach to construction of the signal description, which is invariant to a level of the noise is offered. Efficiency of invariant signals recognition is analyzed.

1 INTRODUCTION

The task of recognition of random noise signals with reference to such tasks as speech recognition (S1ozokai et al., 1998) (Schalkoff, 1992), technical diagnostics of mechanisms on their noise, processing of the biomedical data is considered.

In real conditions of application of recognizing devices for such tasks it is necessary to allow the fact, that on an input of the recognizing device the signal is the sum of a temporary useful signal and one or several disturbance acts. The noncorrelation of a useful signal and disturbances among themselves is supposed. As is known, many tasks of recognition of random signals effectively are solved by transition in spectral area. Therefore in the spectral form representation of a signal, it is possible to write

$$S(\omega) = S_C(\omega) + \sum_{i=1}^k S_{n_i}(\omega), \quad (1)$$

Where S - spectrum of a signal on an input of the classifier, S_C - spectrum of a useful signal, S_{n_i} - spectrum i-th noise disturbance, k - number of noise. Further passing to the description of a spectrum in the vector form as countings on the given set of frequencies $\omega_1, \omega_2, \dots, \omega_d$ and entering concept of the normalized vectors of the spectral description of a signal x_C^0 and noise $x_{n_i}^0$, expression (1) it is possible to write as

$$S = \lambda_0 x_C^0 + \sum_{i=1}^k \lambda_i x_{n_i}^0, \quad (2)$$

Where λ_0 and λ_i - the coefficients defining accordingly power of a signal and disturbances appropriate. Thus the ratio λ_0 / λ_i is the ratio signal / noise for i-th noise.. In case power of a classified signal does not carry the information on the class of the recognized object, parameters λ_0 and λ_i can be considered as hampering parameters.

Since signal distortion parameters (in particular the ratio signal / noise) are unknown, and distortions can reach significant values, there is impossible a correct recognition of signals with the help of the classifier is trained with standard signals, or on the signals subjected to distortions with parameters, distinguished from what take place actually at the moment of recognition. Various approaches to solution of the considered task are known. The most widespread is the method of spectral subtraction of disturbances and its various modifications (Glunder, 1991) (Pattern Recognition and Image Analysis, 2003). A disadvantage of this approach is necessity of knowledge of the ratio signal / noise or obtaining of its estimation. In some cases to receive this estimation it is not possible and accordingly the ratio signal noise appears as hampering parameter to the task of recognition. In such situation natural way is initial creation of the new system of features, wich are invariants (Ben-Arie and Wang, 2002) (Flusser and Suk, 1993) (Glunder, 1991) concerning effect of hampering parameters is represented. Construction of the decision rules is made already at the following

stage, and the class of decision rules that can be used for classification, beforehand to nothing is limited.

2 CREATION OF INVARIANT DESCRIPTIONS OF A SIGNAL AT RECOGNITION ON A BACKGROUND OF DISTURBANCES WITH UNKNOWN POWER

Let's consider a case when on an input of recognition device the signal is, combined with one ($k=1$) additive disturbance. And powers of a useful signal and disturbance are unknown, is equal as the ratio signal / noise q is not known also. Is known sort of the normalized spectrum of power of the noise disturbance, described as vector \vec{x}_n^0 of dimension d . Then the spectral vector of power of a recognized signal \vec{x} can be written as

$$\vec{x} = C_0 \vec{x}_C^0 + C_1 \vec{x}_n^0 \quad (3)$$

Where \vec{x}_C^0 - spectral vector of normalized useful signal, C_0, C_1 - the unknown coefficients depending on powers of a useful signal and disturbance.

If the signal on an input of the classifier is exposed to normalization on power it is easy to show, that coefficients C_0 and C_1 depend only on the ratio signal / noise. Taking into account model of a signal (3), we shall enter in space the initial features X set of transformations

$$G = \{g: g\vec{x} = \lambda_0 \vec{x}_C^0 + \lambda_1 \vec{x}_n^0\}, \quad (4)$$

$$0 < \lambda_0 < \infty, \quad -\infty < \lambda_1 < \infty.$$

Is simple enough to show that these transformations is algebraic group of transformations, caused by two subgroups

$$G_0 = \{g_0: g_0 \vec{x} = \lambda_0 \vec{x}\}, \quad 0 < \lambda_0 < \infty,$$

$$G_1 = \{g_1: g_1 \vec{x} = \vec{x} + \lambda_1 \vec{x}_n^0\}, \quad -\infty < \lambda_1 < \infty.$$

Construction of the invariant description of a signal in the indicated setting is reduced to finding maximum invariant (MI) of transformations group G (Leman, 1959). For construction MI concerning group of transformations G the stage-by-stage

method of construction MI offered by Leman (Leman, 1959) is used. In the beginning it is defined MI concerning subgroup G_1 . It is shown by usage (Geppener and Ekalo, 2002), that it is linear transformations

$$\vec{y} = A \vec{x}, \quad (5)$$

Where the matrix A by dimensions $(d-1) * d$ defines transition in new space Y of features with, dimension $d-1$, and satisfies to a condition

$$A \vec{x}_n^0 = 0 \quad (6)$$

Geometrical interpretation of invariant transformations (5) consists that we select a new coordinate system, one of which axes coincides with a direction of a vector \vec{x}_n^0 . In the further this coordinate is discarded. Thus, is constructed the matrix of transformations A , which rows are the vectors of new axes of coordinates except \vec{x}_n^0 . For construction of new basis the procedure of orthonormalization by Gram-Schmidt, in particular, can be used.

Effect of a subgroup of G_0 induces a subgroup

G^* of the transformations in space Y defined as

$$G_0^* = \{g_0^*: g_0^* \vec{y} = \alpha \vec{y}\}. \quad (7)$$

MI is relative to (7) is usual normalization and can appear as

$$\vec{z} = \frac{\vec{y}}{|\vec{y}|}, \quad (8)$$

where $|\vec{y}|$ - norm of vector \vec{y} , defined, in

$$\text{particular, as } \sqrt{\sum_{i=1}^d y_i^2}.$$

According to the theorem of a stage-by-stage method of construction MI (Leman, 1959), we receive an ending expression for MI concerning group G .

$$\vec{z} = \frac{A \vec{x}}{|A \vec{x}|}. \quad (9)$$

3 EXPERIMENTS

For the experimental research of recognition under the condition of disturbance three etalon disturbances, used for the noise-protected classifier training, were generated. During the experiment distortion of signals was modeled by the disturbance with the given signal to noise ratio q . In the process of training a disturbance with fixed spectrum was used, and for recognition a fluctuation of the disturbance was modeled defined by factor K_{fl} , that shows the ratio of the mean square deviation of the disturbance vector to its mean value. Modeling of two classes of signals for identified objects was fulfilled. Signals were presented by spectral description vectors with dimension 50, number of vectors for each class was equal to 250.

Fig.1 shows the averaged spectra of the generated signals, when Fig.2 shows the etalon disturbances. Experiments were done using the training algorithm based on the Fisher discriminant (Lockwood and Boudy, 1992) with the use of non-invariant features in the form of countings of spectra for two classes of model signals, and the invariant features for three types of disturbances, correspondingly.

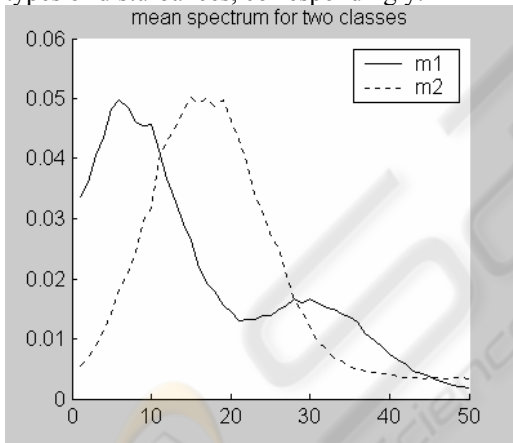


Figure 1: Averaged spectral description.

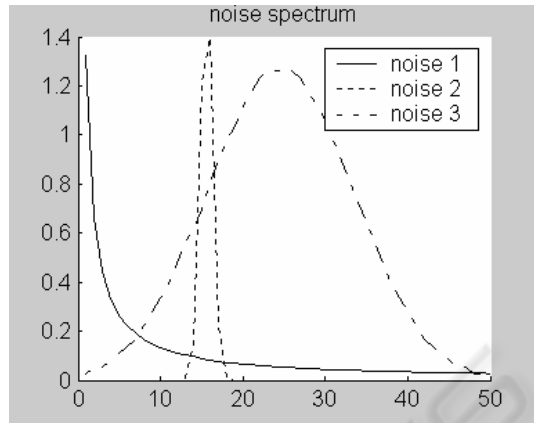
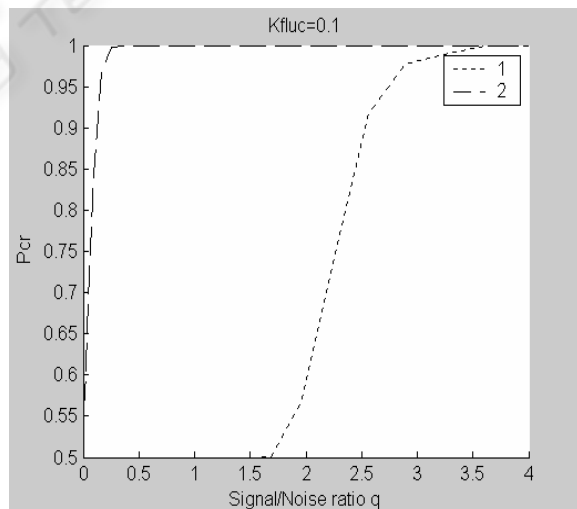


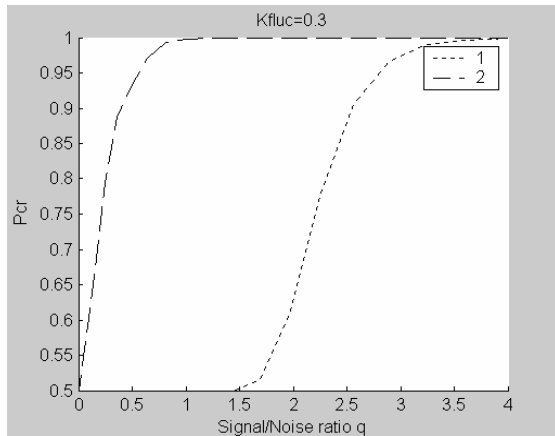
Figure 2: Spectra of etalon disturbances used of classes in the experiment

Figures 3-5 show the dependence of the estimation of correct identification probability P_{cr} on

The signal/noise ratio q . Fig.3 shows the results of the identification experiments with the first type of disturbance (in all figures curve 1 corresponds to the use of non-invariant features, while curve 2 corresponds to the identification with invariant features. Fig.4 shows experimental results of identification modeling, made at the same conditions as in the previous experiments, but for the disturbance type 2, and Fig.5 shows the experimental results for the disturbance type 3, correspondingly.



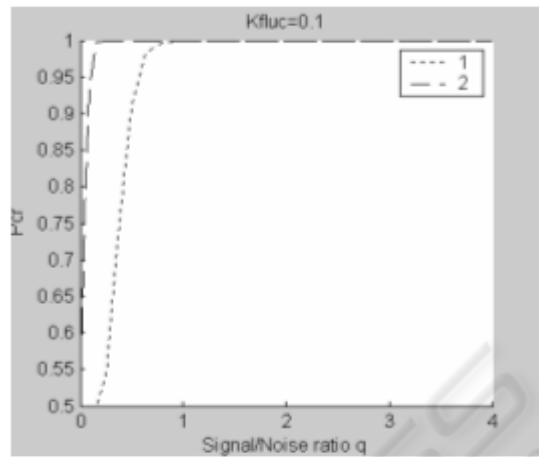
a:



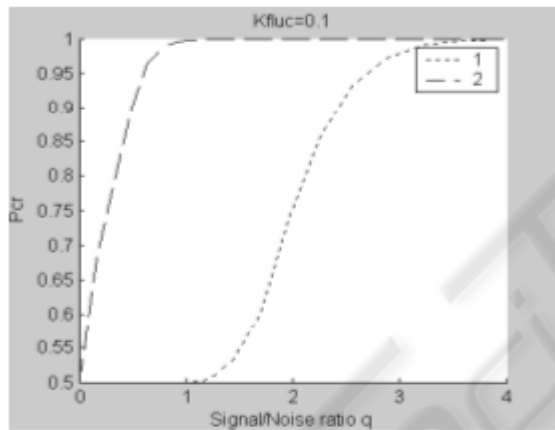
b:

Figure 3: Experiment with a model signal with a disturbance type 1.

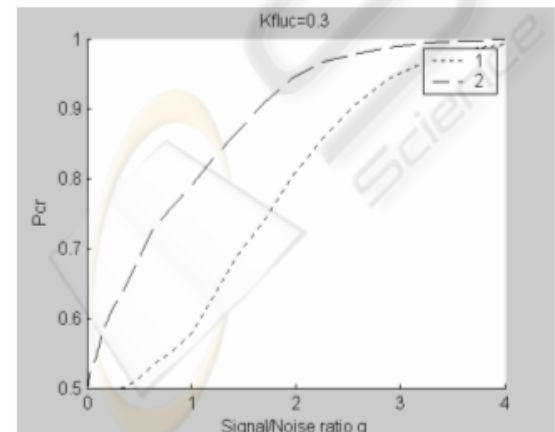
a) $K_{fl}=0.1$, b) $K_{fl}=0.3$



a:



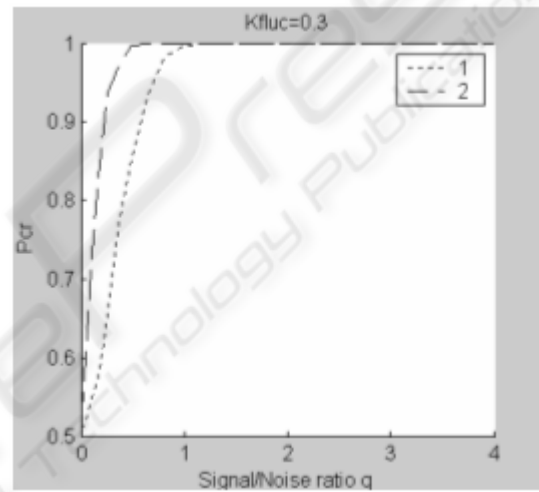
a:



b:

Figure 4: Experiment on the model signal with the disturbance type 2.

a) $K_{fl}=0.1$, b) $K_{fl}=0.3$



b:

Figure 5: Experiment on the model signal with the disturbance type 3.

a) $K_{fl}=0.1$, b) $K_{fl}=0.3$

4 CONCLUSIONS

The results of the experiments can be formulated as follows.

Identification with the Fisher classifier:

- for the given sample of signals under the influence of the disturbance type 1,

The obvious advantage of the noise-protected classifier based on invariant features is discovered, together with the deteriorating quality of identification at the increased fluctuation of the disturbance.(Fig.3).

- Under the influence of disturbances type 2 “noise-protected” dependence is better than non-protected, but is worse than the dependence with the

disturbance type 1 under the same circumstances. (Fig.4).

- under the influence of disturbances type 3 one can fix the least difference between the noise-protected dependence and the non-protected one (Fig.5), but it should be stated that the identification quality is sufficiently good for both cases even at small signal/noise ratio, that is the disturbance of that type is sufficiently "good" for identification.

In addition, similar experiments were done using perceptron algorithm of identification. As a whole, the identification results with invariant features for that algorithm were slightly worse (5-10%) compared with the Fisher classifier, but the difference in the identification quality with the original features was rather big.

Thus, in most cases the investigated method of invariant identification of signals under the influence of disturbances gives practically acceptable results. Nevertheless one should take into account the fact that under the influence of the disturbances of certain types the identification results can be unsatisfactory, so the additional research in the field is necessary.

Conf. on Acoustics, Speech and Signal Processing , p. 208-211

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