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# THE PATTERN RECOGNITION IN ANALYSIS OF VIBROACOUSTIC SIGNAL

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## Abstract
The paper addresses the problem of optimal choice of the most informative diagnostic features of a signal, particularly the vibroacoustic signal. Taking into account that the data are in the form of available attribute vectors, many methods for discriminating between the two classes have been developed. In this paper we review the results of our own research and those found in the literature that are relevant for the solution of diagnostic inference. Special attention is paid on the method of geometrical features selection and blind source separation. The first method presented here uses two criteria related to the ability to separate (isolate) classes of an object's state: the criterion of average scatters and the original criterion of the number of prototypes of classes. The method can be successfully used for initial analysis of input data to a neural network dealing with recognition of patterns of an object's state and classification of an object's state. Concerning blind separation, the method which uses the algorithm of blind equalization (BE) by iterative application of different lengths of equalizers is presented here. This approach allows us to estimate sub-signals in various frequency bands. Main features of this solution include the possibility of discovery and identification diagnostically useful information, even when it is hidden by relatively larger noise and interference.

## INTRODUCTION

Technical diagnosis deals with the evaluation of the technical condition of technical objects (machines). Since the full recognition of technical condition is not always possible or necessary, thus we introduce a certain, defined number of classes of state that correspond to distinguishable states of an object whose recognition is justified due to further procedure to be applied in respect of the object.

Vibroacoustic diagnosis uses the features of vibroacoustic signals, generated during the object's functioning, as the carrier of information on the object's condition. In the analyzed data set there do exist usually certain regularities that can be assigned to individual sources, and in a particular cases to various types of defects or phases of their development. Detection of these regularities can be conducted on the basis of defined rules, approximation algorithms or statistical research.

The influence of the dynamic and kinematic properties on the process of generation of vibroacoustic signal results in a situation whereby the analyzed set of data is usually characterized by certain redundancy. Moreover, part of the data is often not essential from the point of view of the object's condition recognition. In order to overcome the problems associated with the big volume of data one should reduce the dimensions of the data set. This can be done by selecting a subset of data (features of signals) which describes the condition of an object equally well as the original full data set. The process is called feature selection. It is particularly desirable to find such a subset of data in which the exposition of the occurring regularities and divisions into classes of state is particularly clear and simple from the point of view of the process of creation of classification algorithms. This paper presents an original geometrical selection method which relies on the criteria of separation of classes of state in the data space.

In the paper we have moreover accounted for the occurrence of additional difficulties, that is the fact that the registered vibroacoustic signals are usually composed of many signals generated by the object, with only some of these signals being the ones we want to analyze. The noise registered along with the information-carrying signals disturbs the values of isolated features of the information signal, thus making extraction of diagnostic information more difficult. Extracting the diagnostically-useful information from the registered vibroacoustic signal is substantially easier if we carry out specific separation of the information-carrying signal from the noise.

Among the numerous methods and techniques of noise elimination it is the so-called. Blind Equalization (BE) that is worth noting. It plays an important role in the field of digital communication and thanks to the good results of signal separation it gains growing recognition. In contrast with the conventional adaptation filtering, this method is "blind," that is it works without the awareness of the information or disturbing signals and without knowing how these are mixed. Extraction of the information-carrying signal is possible thanks to using a "blind" filter with accordingly selected parameters.

## GEOMETRICAL FEATURE SELECTION

An ordered series N of values $\{x_1, x_2, ..., x_N\}$ of features of vibroacoustic signals generated during operation of the diagnosed object is called the observation vector of an object's state. From geometrical point of view the components of the observation vector of an object's state (the values of signal features) can be treated as coordinates defining a point in the N-dimensional object's state observation space. Thus, each state of an object has its pattern in the observation space of an object's state.

From geometrical point of view the classification algorithm divides the observation space into disjoint decision regions corresponding to individual distinguishable states of an object (classes of state of an object). In the machine learning methods, the topography of decision regions is created with the use of a certain set of teaching examples, called the teaching set and composed of patterns whose proper classification we know. Assuming that the patterns of similar states of an object are closer to each other in the observation space than the patterns of different states of an object, thus the areas of occurrence of the patterns belonging to individual classes make up the decision regions corresponding to respective classes. The classification of a new pattern takes place based on its location in relation to thus generated decision regions – a pattern is treated as belonging to a given class if it is located in the decision region corresponding to this class. Classification of a pattern of an object's state corresponds to qualification of the state of the controlled object to a specified class of state.

As a result of the selection conducted for an N-element set of signal features we arrive at a reduced, M-element set of features (where M<N), which corresponds to the new M-dimensional observation sub-space of an object's state. The issue of selection of signal features can thus be narrowed down to the search for such a sub-space of the original observation space of an object's state in which the topography of decision regions is most favorable from the point of view of separation of an object's classes of state. Assuming that certain correlation exists between the degree of separation of decision regions and the general usefulness of the features for classification purposes, for the needs of evaluating the usefulness of the features we can rely on the criteria of separation of decision regions in the observation sub-space created by these features, namely the criterion of average scatters and the criterion of number of prototypes of classes [1, 2, 3].

**Criterion of Average Scatters**

The criterion of average scatters, being the modified Sebeysten [7] criterion, relies on the concept of evaluation of the scatter of patterns, occurring within a given observation space, inside and between the decision regions and is formulated in the following way:

$$K_S = \frac{\overline{R}_M - \overline{R}_W}{\overline{R}} \tag{1}$$

where: $\overline{R}$ - the average scatter of patterns in the observation sub-space, $\overline{R}_M$ - the average scatter between the regions (average interclass scatter), $\overline{R}_W$ - the average scatter within a region (average intraclass scatter).

We are looking for such an observation sub-space which will give the biggest value of this criterion. This way we set preference for the object's state observation sub-spaces with big relative distances between the decision regions and with a simultaneous, relatively big internal concentration of each of these regions. The non-dimensional form of the criterion enables comparison of various observation sub-spaces even in a situation of existence of big differences between the dimensions of individual components of the object state's observation vector.

**Criterion of the Number of Prototypes of Classes**

The criterion of the number of prototypes of classes relies on the concept of evaluation of the degree of penetration in a given observation sub-space of decision regions and complexity of "contact areas" of the regions [3]. The prototypes of class are the selected patterns which are the representatives of a given class. The prototypes can be in a sense identified with the patterns "separating" the decision regions in the observation sub-space (the "boundary" patterns of these regions). It should be stressed that individual observation sub-spaces can have varied prototypes of classes. The number of prototypes of classes in a given observation sub-space is the sum of the number of prototypes of all classes. The technique we applied for determining the prototypes [3] results in a situation that the number of prototypes of classes cannot be smaller than the number of classes (each class must have at least one prototype) and not bigger than the number of learning examples (each learning example can be a potential prototype).

We are looking for such an observation sub-space which has the smallest number of prototypes of classes. This way we set preference on the observation sub-spaces with less complex "contact surface" of the decision regions. The observation sub-spaces which are evaluated poorly are the ones in which there occurs overlapping of decision regions.

**Evaluation of Feature Sets (Feature Selection)**

Each set of a signal's features (any object's state observation sub-space) can be subjected to evaluation of diagnostic usefulness by designating the values of two criteria: criterion of average scatters ($K_s$) and the criterion of number of prototypes of classes ($N_p$). It is convenient to include the results of the evaluation of individual observation sub-spaces (individual sets of features) cumulatively in one figure (Figure 1).

Each point (+) represents a certain observation sub-space. In the upper left corner we see (as marked with a bold circle) the best observation sub-space (with the big value of $K_s$, and small value of $N_p$), in lower right corner we see (marked with a bold square) the worst observation sub-space (with the small value of $K_s$ and the big value of $N_p$).

Evaluation of individual sets of signal features becomes the basis for selecting the relevant sets, which as a result leads to the selection of certain features of signals which are best from the point of view of the assumed classification. Since a defined set of signal features corresponds to each observation sub-space, thus the set of these features of signals which were used for establishing the best observation sub-space is the select, best group of signal features from the point of view of the assumed classification. Thus the results of evaluation of sets of features are the criterion for selecting the features.

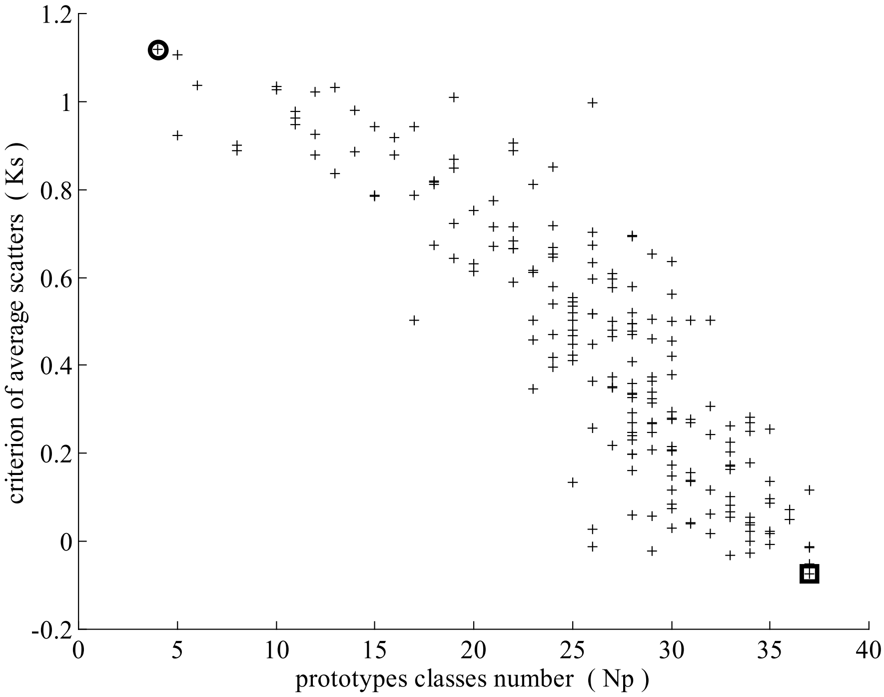


*Figure 1 – Exemplary results of evaluation of the observation sub-spaces [3]*

## BLIND EQUALIZATION

The fundamental idea of Blind Equalization (BE) is the ability to obtain special characteristics of a filter while only relying on the registered signals without any knowledge of their sources and paths of propagation. As a result of fine results of signal separation in the state-of-the-art digital communication, blind equalization gains increasing recognition and at the same time demonstrates big potential in diagnostic systems of machines. The application of the blind equalization method for separation of complex vibroacoustic signals for the needs of diagnosing of technical objects would bring in a new quality in this field.

At present there exist two algorithms for solving the blind equalization issue. One of them is the algorithm called the super-exponential method. It has been the first technique which enabled solving the BE problem [4, 10]. The second approach is represented by the increasingly popular EVA (eigenvector algorithm) method. This solution of blind equalization has been discovered and expressed as a theory related to eigenvectors in 1994 [5].

The discrete equalization model describing the EVA method is presented in Fig. 2. The original source signal *s(k)* is described by the zero average value, variance $\sigma^2 = \mathrm{E}\left\{(s(k))^2\right\}$, skewness $\gamma_3 = \mathrm{E}\left\{(s(k))^3\right\}$ and kurtosis $\gamma_4 = \mathrm{E}\left\{|s(k)|^4\right\} - 2\sigma^4 - \left|\mathrm{E}\left\{s^2(k)\right\}\right|^2$.

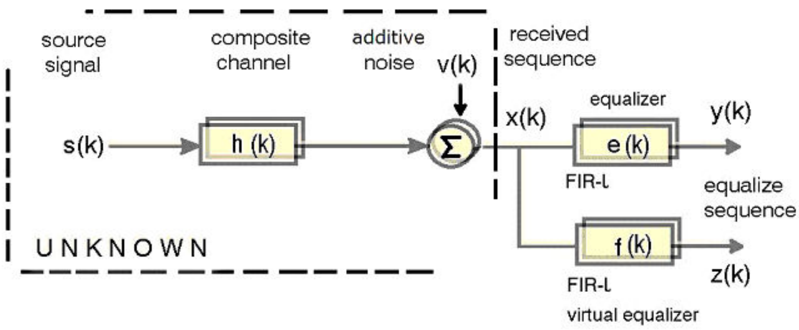


*Figure 2 – Basic configuration of EVA algorithm*

The model accounts for the occurrence of unknown propagation paths *h(k)* of a signal which by assumption are considered by us to be invariable in time, at least during a short period of time. Such a method of signal propagation can be presented as FIR (finite impulse response) filter $h(k) = h(0),...,h(l)$, where $l$ is the order of the filter. Apart from the linear distortion, the model accounts for the occurrence of a disturbing signal represented by an independent additive white Gauss noise *v(k)* with a zero average value.
The signal *x(k),* registered by the sensor, is described by the following relationship:

$$x(k) = h(k) * s(k) + v(k) \quad \text{or} \quad x(k) = \sum_{l=1}^{L} h(l)s(k-l) + v(k) \tag{2}$$

To reconstruct the source signal *s(k)* from the observed signal *x(k)* we need to find the optimum reverse filter *e(k)* which will fulfill the following relationships:

$$y(k) = e(k) * x(k) \quad \text{or} \quad y(k) = \sum_{l=1}^{L} e(l)x(k-l) \tag{3}$$

in such a way that *y(k)* can be the recovered original source signal *s(k)*.

Additional, virtual filter f(k) is used in the EVA method. This filter is of the same order as the filter e(k). It is used for the purpose of estimating the output of the reference z(k):

$$z(k) = x(k) * f(k) \tag{4}$$

EVA algorithm has been noted as an interesting tool for vibroacoustic diagnosis of technical objects in numerous publications [6, 9, 11]. Periodical or pulse signals are the two types of signals that mainly appear in the case of failures of machines. Research confirms that EVA, as a blind equalization solution, is effective in identification of such signals from among the interference and noise.

Effective operation of EVA algorithm depends on the relevant selection of the length of the filter, the size of the sample subjected to analysis and the number iterations. The higher order filters demonstrate propensity to eliminate certain periodical components of the original signal. The big size of the sample increases not only the resolution of the result but also the requirements for computational power. Increase of the number of iterations can improve the result of separation but at the same time in increases the time required for calculations. In order to achieve satisfactory results from the practical application of blind equalization by means of EVA algorithm, one has to carefully consider and account for all these issues.

## SUMMARY

The experiments we have conducted prove that out of the two criteria used it is the criterion of the number of prototypes of classes that should be given more attention while treating it as the basic criterion [1]. It is even permissible to rely on this criterion only.

Finding the best observation sub-space calls for evaluation of all observation sub-spaces that can be created. The general number of such potential observation sub-spaces that are possible to be created can at times be too big to enable evaluation of all of them (due to the time required for calculations). In such a case one should adopt some strategy of selecting the observation sub-spaces intended for evaluation. The advantage of the presented method is that the calculations concerning individual observation sub-spaces are autonomous and can be performed for any sub-space separately. This offers the possibility of distributing the calculations to many computations centers, which significantly shortens the time required for the calculations.

The experience of the authors shows that the presented method of feature selection can be successfully used for initial analysis of input data for a neural network involved in pattern recognition. First we have the extraction of the features which carry information that is valuable and important from the point of view of its usability in the process of recognition of individual classes and then the neural network performs the classification while relying on these classes. Thanks to rejecting the data that does not contain the information which is interesting for us, we reduce the size of the neural network (smaller number of network input points) and improve the efficiency of its operation. The correctly selected input data substantially facilitate the proper and fast training of a neural network. Poor evaluation of the applied set of input data can in turn explain the lack of success in the learning of a neural network.

What is equally interesting is the possibility of using the algorithm discussed in this paper for determining the prototypes for selecting the data used in the process of neural network training, that is for the creation of a training set for such a neural network. The training data selected in such a way is located close to the individual sections of the hyper-surfaces that divide the data space in decision regions. In such a case the algorithm can be used even when the distribution of the data in a data space is multi-modal while the decision regions are non-convex. Such a selection of training data facilitates proper training of the neural network and reduces the size of the training set while restricting it to designated prototypes of classes.

The blind equalization method presented here is relatively new and that is why there still exist numerous possibilities of its development. The blind equalization method described here by the EVA algorithm operates in SISO (Single Input Single Output) configuration, which is a serious limitation for using this method in the diagnosis of actual technical objects. Further research needs to be conducted in order to introduce the required improvements that will enhance the effectiveness and universality of EVA algorithm and which will turn it into even more useful tool for vibroacoustic analysis of technical objects. Should these efforts be completed with a success, then this would certainly be a kind of a breakthrough in the diagnosis of machines.

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