VPS VIBRATIONS IN PHYSICAL SYSTEMS

DOI: 10.21008/j.0860-6897.2024.2.14
Vibrations in Physical Systems, 2024, 35(2), 2024214

Identification of errors in the digital transmission paths of radio stations

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Abstract The radio stations now use a hybrid method of broadcasting. Transmission between the studio and the transmitter is digital. In the transmitter digital signal is converted to analog and this signal is transmitted by AM or FM modulation. The identified problem are transmission errors in the digital path. Single errors in transmission are not unusual and happen in most cases systems. However, repeated and grouping errors are usually a sign of track damage transmission line and require intervention. In the article presents an example solution to automatically detect some errors that manifest themselves in the identified way. To identify transmission errors, basic statistical methods were used that allowed to create a reference data set on the basis of which it is possible to identify the fact occurrence of an error based on patterns and algorithms from the machine learning area. The environments related to the radio industry are keenly interested in researching this phenomenon because now is not available solutions allowing for automatic detection and identification of this type problems.

Keywords: machine learning, noise, sound distortion, radio line, sound samples, classifier, phenomenon detection.

1. Introduction

Digital transmission methods have revolutionized the field of radio and television, making it possible the use of hybrid techniques in which the signal is transmitted between the studio and the transmitter in digital format before being converted to analog and modulated with AM or FM [1]. However, these advances also introduced challenges, particularly in the form of transmission errors. Automatically detecting and resolving these errors is critical to maintenance reliable radio transmissions [2].

The article presents a solution for automatic transmission based error detection about statistical methods and machine learning algorithms [3]. The goal is to create a reference dataset and developing a classification system that will allow the different types to be identified transmission errors. Such research is of great interest to the radio industry, because it is on the market there are no solutions that allow automatic implementation of interference detection based on the signal resultant [4, 5].

Although the problem is noticed by technical personnel operating radio stations, there are no direct references to it in the literature. Related and similar issues are considered and, on their basis, the current state of knowledge is recognized.

In order to carry out the research, artificial disturbances were introduced to various types of signals generated to simulate actual transmission errors. Audio plays were used for the analysis radio, relaxing music, rock music and conversations. These disruptions included clippings, white noise, Gaussian noise, loops and silence cases [6] Signal analysis focused on extracting statistical features from extracted parts of the signal, such as mean, median, standard deviation, kurtosis, and first discrete difference to distinguish between signal types and transmission errors [7].

Techniques based on machine learning methods are used in industry, among others, in devices where it is necessary to maintain continuous operation. Such devices are engines. Based on the analysis of their operation, a system was developed that enables the detection of device operation disruptions based on the analysis of the current consumed and the detection of short circuits. The activities allow for the detection of, for example, damage to the bearings or the structure of the entire device [8].

Systems that use machine learning elements must adapt during operation to be able to respond appropriately to events. When creating a system, it is necessary to pay attention to the phenomenon being examined, whether it occurs at a specific point or in a wider range, and what features will allow it to be defined [9].

Machine learning is used in traffic modelling. During traffic analysis, it is necessary to follow the pattern and reproduce the developed patterns. Machine learning systems are ideal for these applications because they can reproduce the actions for which they have been trained not entirely precisely, but with an acceptable approximation. To train the system, it is necessary to collect an appropriate number of samples, which will allow the development of appropriate patterns [10].

A frequently chosen method, not only for detecting irregularities in signals in real time, are methods based on deep learning [11]. This approach, although usually effective, does not provide insight into the nature of the problem, but only provides a potentially useful solution. Although the results of such systems are usually acceptable, it is impossible to be sure how such a system will respond to unknown input data. In such cases, solutions based on knowledge of the essence of the phenomenon are more reliable, although unfortunately usually with lower effectiveness.

The results of these studies have important implications for the radio industry as they contribute to automation of detecting and solving transmission errors. Thanks to the development of efficient classification system, this test improves the reliability and performance of radio systems broadcast [8, 9].

2. Materials and methods

The available material containing real cases of errors and the resulting interference was not quantitatively sufficient to conduct the research - transmission errors, although they are a problem, do not occur very often. Therefore, the research was carried out with the use of artificially introduced interference to several types of signals with different content and dynamics. The nature of the errors corresponded to the original cases registered in the real transmission paths.

Each of the tested signals was a radio recording containing: radio drama, relaxing music, rock music, and conversation. The interference was stimulated by typical problems occurring on transmission lines and indicated by the technical service of radio stations:

- cut – cutting out (losing) a single packet with data, signals contained in the packets preceding and following the lost packet are reproduced without interruption, omitting the lost data;
- white noise – damage to the data packet during decompression generates pseudo-random noise, the nature of which corresponds to the signal generated by the pseudo-random number generator;
- Gaussian noise – noise of this type has its source typically in natural processes and has not been observed in the samples of real disturbances, in the tests it was used for comparative purposes for other types of disturbances;
- loop – repetition of the packet, i.e. replaying the same signal fragment at least twice;
- silence – replacing a damaged or lost data packet with samples of equal value, typically zeros.

For each type of signal, interference of each type was introduced in several places. The length of the inclusion was arbitrarily set at 1024 samples. The sample rate was 44100 S/s.

2.1. Features extraction

The signal analysis included the division of the signal into fragments and the extraction of features that are input data for the classification system. The length of the window constituting the basis for the calculation of features was set at 1024 samples. The window was moved along the signal in steps of 16 samples (Fig.1).

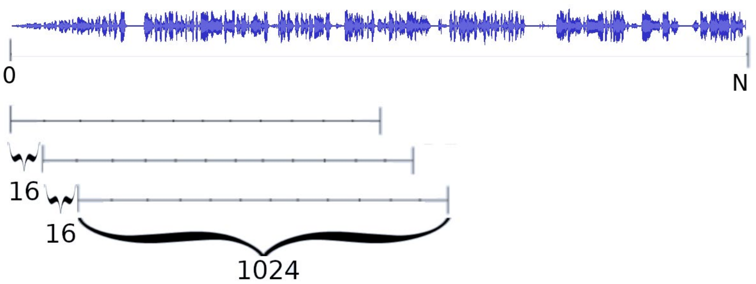

Figure 1. Splitting the signal into fragments.

As features for the classification system, the basic statistical parameters of the signal were adopted, defined by the following formulas:

$$\overline{x} = \frac{x_1+x_2+\cdots+x_n}{n} = \frac{\sum_{i=1}^{n} x_i}{n}, \tag{1}$$

$$M_e = \frac{1}{2}\left(x_{n/2} + x_{(n+1)/2}\right), \tag{2}$$

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \overline{x})^2}{n-1}}, \tag{3}$$

$$K = \frac{n(n+1)}{(n-1)(n-2)(n-3)} \sum_{i=1}^{n} \left(\frac{x_i-\overline{x}}{\sigma}\right)^4 - \frac{3(n-1)^2}{(n-2)(n-3)}, \tag{4}$$

$$\dot{x}_i = x_i - x_{i-1}, \tag{5}$$

where: $\overline{x}$ – mean, M_e – median, σ – standard deviation, K – kurtosis, n – number of samples, x_i – i-th sample, $\dot{x}_i$ – first discrete difference.

The process of feature extraction was carried out. Based on the results obtained, the process of building a vector was carried out, based on which the decision about the analysed signal sample is made. The data in the vector are in the random order that was created during the algorithm creation process. The order of the described features does not matter when it comes to the classification process. The vector is created based on fragments with a length of 1024 samples. Features such as mean, median, standard deviation, Kurtosis and first discrete difference are determined. This data allows for understanding the physics of a given phenomenon and its identification using designated features.

Vector construction -> [AVG, Median, Standard Deviation, Kurtosis, Maximum value of the first discrete difference]

The set of vectors built on the basis of reference samples constitutes the training set for the classifier. The number of vectors of each class in the set is 33528. The number of vectors describing the class without disturbances is the same in each set as the number of vectors describing the class with disturbances (the sets are quantitatively balanced and contain 16764 samples with disturbance and the same number of samples without disturbance). Each vector calculated on the basis of the tested signal is classified using a classifier built on the basis of the reference set.

Table 1 presents exemplary values of the calculated features for two fragments from the recording of a conversation and white noise. The juxtaposed values show that they differ significantly from each other and therefore can be potentially useful in the process of signal classification.

Table 1. Feature values calculated for random fragments of two types of the tested signal.

Type of sound	mean	median	deviation	kurtosis	the maximum value of the first discrete difference
conversation	0.65	0	12.69	5.07	43
white noise	21.68	-361	2371.72	96.64	29940

2.2. Classification

The classification was carried out in two stages. First, the successive fragments of the signal were classified, and then the classifier indication sequence was filtered and thresholded.

Nearst Centroid form sklearn was used. The input vectors of the model describing the correct signal were randomly selected from all the vectors calculated for the correct signal. Their number has been reduced in order to balance the number of positive and negative sets. The input vectors describing the interference events came from the fragments within which the interference was located. Each type of recording was analyzed separately.

The NC classifier belongs to the group of minimal distance classifiers and in the learning process it is based on the calculated centers of gravity of sets or their separated parts. The tested element is assigned to the class whose center of gravity or one of the centers of gravity of the subsets of a given class is closest to the tested vector [12].

The sequence of indications at the output of the classifier was filtered with a low-pass filter (unipolar recursive filter, IIR) and then thresholded (Fig. 3). This solution made it possible to eliminate single, incidental incorrect indications of the classifier, reducing the number of false-true indications. The method of signal processing from the classifier output is shown in Fig. 3.

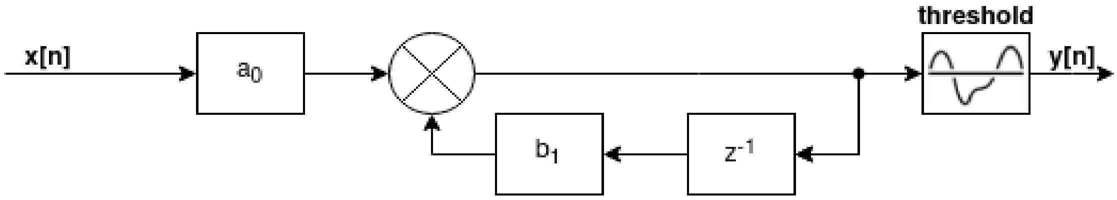

Figure 2. Flowchart of the process eliminating incidental false positive indications, a_0 and b_1 are the coefficients of the recursive filter, z^{-1} coefficient is the delay block. The filter contains an additional block - the thresholding process.

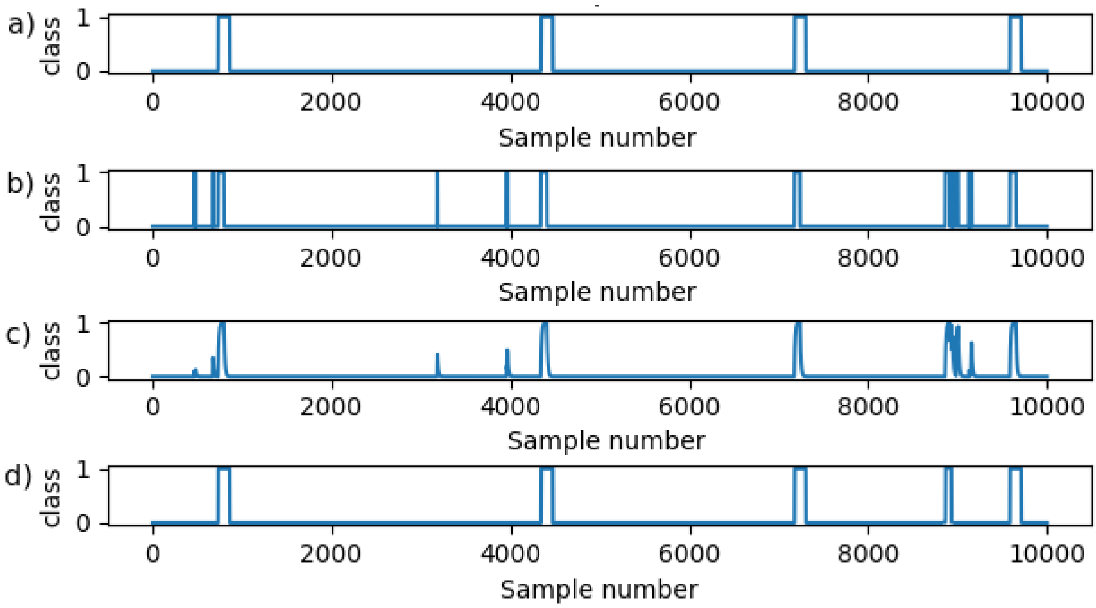

Figure 3. The process of eliminating incidental false-true indications: a) real locations of disturbances, b) classifier indications, c) classifier indications after low-pass filtering, d) system indications after thresholding.

The filtration process sometimes also eliminates true-true indications, however, the overall balance of the process is positive - a significant number of false-positive indications are removed with single instances of true-true indications. The effect of the system operation on a fragment of a radio drama with white noise inclusions is shown in Fig.5.

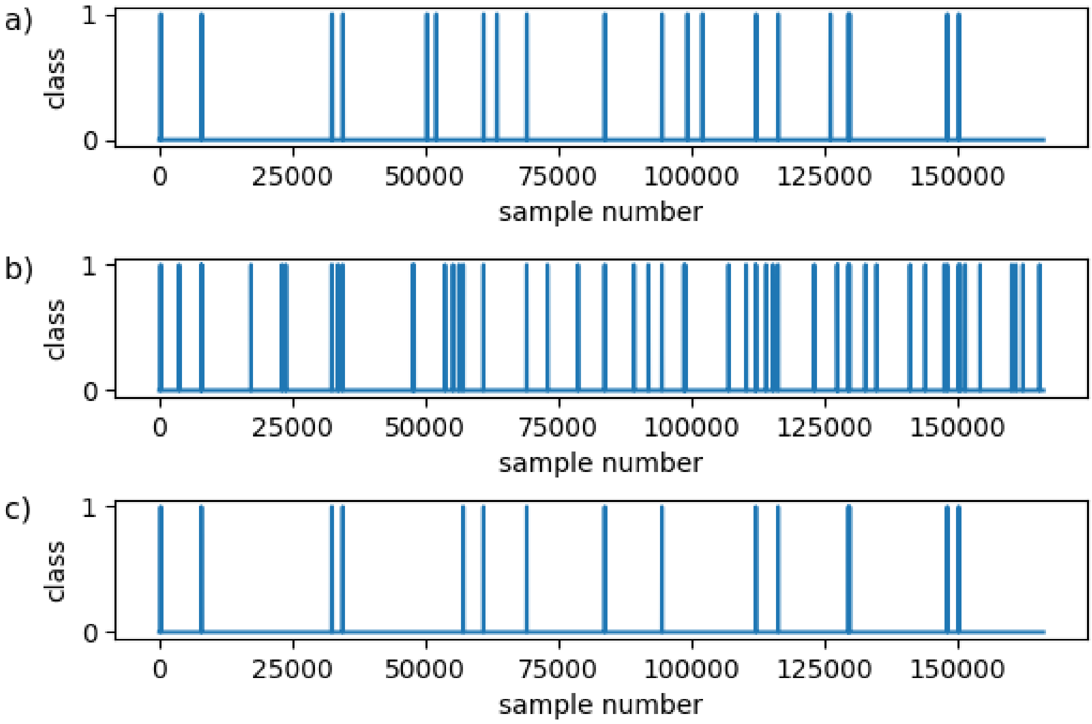

Figure 4. An example of the result of the system operation for the radio drama signal and white noise inclusions: Figure a) shows actual error occurrences. The figure marked b) shows the data after leaving the classifier. The figure marked c) contains information about the error obtained after the filtration process.

2.3. Assessment of classification quality

The quality of the classification was assessed on the basis of the error matrix and the following quality indicators: PPV, TPR, FNR and F1-score. Due to the specificity of the problem, i.e. a significant unbalance of the set due to a very large number of vectors describing true-false cases (i.e. those in which the disturbance does not occur and the system has correctly classified), the calculation of the TF field in the error matrix and the resulting indicators was abandoned. The adopted measures describe the process in a sufficient way.

PPV - positive predictive value, or in other words, this indicator describes the effectiveness of the test, its values range from 0 to 1, where the value of 1 means 100% correct and 0 means 0%, if this indicator reaches values closer to 1, the better the test works and such behavior of the parameter is desirable . This indicator can be calculated using the following formula:

$$PPV = \frac{\sum TP}{\sum TP + \sum FP}. \tag{6}$$

TPR - Percentage of correct positive predictions means that this indicator reflects the number of correct samples classified as correct samples in the literature. This indicator is defined as sensitivity and its values range from 0 to 1. The higher the value, the better, as it means the more correct operation of the classifier. This indicator can be calculated using the following formula:

$$TPR = \frac{\sum TP}{\sum TP + \sum FN}. \tag{7}$$

FNR - Percentage of incorrect negative predictions This indicator represents samples that are correct and were classified incorrectly. that is, they were treated as samples containing error. This indicator takes values from 0 to 1, the closer the value to zero, the better in the case of this parameter. This indicator can be calculated using the following formula:

$$FNR = \frac{\sum FN}{\sum TP + \sum FN}. \tag{8}$$

F1- Test accuracy In statistical classification analysis, the F-score is a measure of test accuracy. Which is calculated based on the precision and repeatability of the test, where precision is the number of true positive results divided by the number of all positive results, including those incorrectly classified, and repeatability is the number of true positive results divided by the number of all samples that should be classified as positive. Precision is also called positive predictive value. The closer this value is to 1, the better. This indicator can be calculated using the following formula:

$$F1 = \frac{2 * \sum TP}{2 * \sum TP + \sum FP + \sum FN} \tag{9}$$

An example confusion matrix for a radio drama signal and white noise inclusions is shown in Tab.2.

Table 2. An example confusion matrix for a radio drama and white noise inclusions.

	Test result	
	Positive classification	Negative Classification
Positive state	15	5
Stan negative state	1	

3. Results and Discussion

As a result of the conducted tests, the values of classification quality indices were obtained for each of the tested types of signals in combination with each of the tested types of interference. A summary of the results is presented in Tab.3.

Table 3. Summary of research results.

Type of sound	Type of insertion	PPV	TPR	FNR	F1
Radio drama	Cut	0.05	0.70	0.30	0.10
	White noise	0.79	0.95	0.05	0.86
	Gaussian noise	0.94	0.75	0.25	0.83
	Loop	0.04	0.65	0.35	0.07
	Silence	0.05	0.85	0.15	0.07
Relaxing music	Cut	0.03	0.65	0.35	0.05
	white noise	0.76	0.65	0.35	0.70
	Gaussian noise	0.94	0.75	0.25	0.83
	Loop	0.04	0.85	0.15	0.08
	Silence	0.04	0.90	0.10	0.07
Rock music	Cut	0.04	0.80	0.20	0.08
	white noise	0.55	0.55	0.45	0.55
	Gaussian noise	0.89	0.40	0.60	0.89
	Loop	0.04	0.90	0.10	0.07
	Silence	0.03	0.80	0.20	0.06
Conversation	Cut	0.05	0.85	0.15	0.09
	White noise	1.00	1.00	0.00	1.00
	Gaussian noise	1.00	1.00	0.00	1.00
	Loop	0.05	0.65	0.35	0.09
	Silence	0.05	0.70	0.30	0.10

Depending on the type of signal and interference, the results were significantly different in terms of quality. The best quality was obtained for interference in the form of noise, with Gaussian noise giving better results. The exception is the radio drama, in which white noise turned out to be better. This is probably due to the content of sounds of natural origin in the radio drama signal, which are the background for the broadcast content (e.g. wind, splashing water, etc.). The worst quality for noise was obtained in combination with rock music. This is due to the content of a large number of components similar to noise (e.g. a modified sound of an electric guitar, drums, etc.).

The system turned out to be basically useless in the case of other types of interference for all types of signal. This is due to the lack of characteristic statistical features distinguishing these inclusions. Preliminary test results placing hope in a first discrete difference that detects sudden changes in value between the signal and the insertion have not been confirmed. This feature generates single pulses that are leveled in the low-pass filtering process.

4. Conclusion

The research involved the use of a simple statistical model combined with a classifier to detect typical interferences in digital transmission paths used to send radio broadcasts from the studio to the transmitter. The adopted model made it possible to achieve the goal in a limited number of cases. Only disturbances of one type, i.e. noise resulting from errors during data packet decompression, were detected satisfactorily. Other types of disturbances did not allow for the construction of a properly functioning decision-making model.

Due to the lack of characteristic statistical features distinguishing loop, cut or silence disturbances from the useful signal, it is necessary to use other methods of feature extraction. It can be an autocorrelation of signals or an extended analysis based on a first discrete difference.

As a result of the conducted research, it was noticed that each type of disturbance should be handled by a separate classification system, operating on the basis of individually selected sets of features and the data processing process, both before and after classification. In the course of further work, it is planned to modify and develop the system in this direction.

Identification methods based on deep machine learning methods were consciously abandoned. Identification was based on features such as mean median kurtosis or standard deviation. Such activities are aimed at finding the physical characteristics of the disturbance and its identification using basic statistical methods. There are systems on the market based on deep learning systems that allow for the identification of, for example, aircraft flights - these systems are trained with data. The user does not think about how to identify the disturbance - the system finds the features itself, but there is no information about what values indicate the occurrence of the disturbance or the occurrence of a given phenomenon.

Additional information

The authors declare: no competing financial interests and that all material taken from other sources (including their own published works) is clearly cited and that appropriate permits are obtained.

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