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HISTOGRAM-BASED FEATURE EXTRACTION TECHNIQUE APPLIED FOR FAULT DIAGNOSIS OF ELECTRONIC CIRCUITS

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Abstract - In this paper we discuss and compare two feature extraction techniques: histogram-based and Principal Component Analysis. Comparison is done on an analog filter fault diagnosis example performed in the frequency domain. Both techniques are implemented in a neural network system for the off-line diagnosis of electronic analog and mixed-signal circuits. The numerical and experimental examples of frequency domain ANN-based testing of filter are presented to demonstrate the usefulness of the histogram approach.

Keywords: analog fault diagnosis, feature extraction, histogram-based technique.

1. INTRODUCTION

Diagnosis of analog electronic circuits provides an extremely difficult challenge. This is due to the problem of modelling of faulty circuits, the tolerance of components, the problem of limited number of test points, and the nonlinear nature of the relationship between the circuit responses and the component characteristics, even if the circuit is linear. Among the various techniques suggested in the literature, the most widely appreciated in practical engineering applications is the taxonometric approach that employs a fault dictionary. The fault dictionary is built at the before-test stage by means of Monte Carlo simulations of the circuit under test (CUT), under nominal and faulty conditions. In the diagnostic process, the measured circuit responses are compared to the responses corresponding to each potential fault condition, stored in the dictionary. The state of the circuit is then reported. In the recently published works [1-12] the most popular for creating the fault dictionary, memorizing and verifying it, is using an Artificial Neural Network (ANN).

The neural-network-based diagnostic system applied for analog electronic circuits is, besides of measuring equipment, composed of feature extractor and a classifier [13]. The former is used to reduce the measurement data and extract diagnostically relevant features, the later is used to localise a faulty element. There are several feature extraction techniques reported in the literature: Principal Component Analysis (PCA), Fourier Transforms, Wavelets. The PCA technique, also known as the Karhuen-Loeve transform, works as a feature extractor in many applications. Its main advantage is effective data compression.

As it has recently been demonstrated by one of the author [14], an alternative is to perform feature extraction task with computationally extremely simple histogram-based method. This paper discusses the possibility of using histogram for fault location in electronic circuits. We compare histogram-based technique (HIST) and Principal Component Analysis method on an example of analog filter fault diagnosis, performed in the frequency domain. Both techniques are implemented in a neural-network-based diagnostic system.

In the following section we describe the architecture of the system. Details of two different feature extraction techniques are given in Section 3. In Section 4 we present three neural network classifiers and show results of its training with two kinds of compact data. Section 5 presents results of experiments with the real circuit.

2. ARCHITECTURE OF THE DIAGNOSTIC SYSTEM

The architecture of the diagnostic system developed by authors is shown in Fig. 1. In the before-test stage all effort is focused on the problem of the circuit under test modelling, the extraction of effective features and training the neural network. The training patterns are collected from the faulty circuit responses using the Matlab model of the CUT, Monte Carlo simulation and the same feature extraction technique that will be used in the testing.

The measuring part of the system provides diagnostic information from the circuit under test input/output measurements performed in the frequency domain. A test signal is applied to the CUT and the response is analyzed by the HP 4192A LF Impedance Analyzer. The measurements on a real circuit are sent from analyzer, via IEEE 488 interface bus, to the computer PC. We extract significant features (signatures) from the responses and use them as inputs to the neural network. The ANN, that has been previously trained to classify single faults on the CUT, reports the diagnosis.

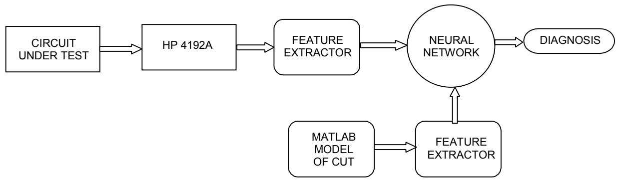

Fig. 1. The neural-network-based diagnostic system architecture

3. FEATURE EXTRACTION TECHNIQUES

The selection of the features that are going to be used in ANN training is important step at the before-test stage. The importance of such task stems from the fact that these features should adequately represent the diagnosis problem.

Each circuit response is composed of samples of two measured parameters - magnitude and phase, taken at all test frequencies. So, it is represented by $2f$ - element vector of measured data, where f is the number of test frequencies. Since the dimension of vector is large we need to extract relevant diagnostic features in compressed form referred to as a fault signature. The goal of the feature extraction technique is to reduce the number of elements in the signature with acceptable loss of information. An effective procedure for performing this operation is Principal Component Analysis.

3.1. Principal Component Analysis

Compression of data by means of PCA is achieved by projecting each data vector along the directions of the eigenvectors of the covariance matrix of data. In general, the PCA technique transforms n vectors $(\boldsymbol{x}_1.\boldsymbol{x}_2...\boldsymbol{x}_i...\boldsymbol{x}_n)$ from a s-dimensional space to n vectors $(\boldsymbol{x}_1^{'}.\boldsymbol{x}_2^{'}...\boldsymbol{x}_i^{'}...\boldsymbol{x}_n^{'})$ in a new, r - dimensional space of reduced dimensionality as

$$\boldsymbol{x}_i^{'} = \sum_{k=1}^{r} a_{k,i}\boldsymbol{e}_k \ , \qquad (1)$$

where: n is the number of the observation vectors $\boldsymbol{x}_i$, $a_{k,i}$ are the projections of the original vectors $\boldsymbol{x}_i$ on the eigenvectors $\boldsymbol{e}_k$, corresponding to the r largest eigenvalues of the $s \times s$ covariance matrix for the original data set defined as

$$\boldsymbol{C} = E[\boldsymbol{x}_i \boldsymbol{x}_i^T] \quad \text{for } i = 1 \text{ to } n \ . \qquad (2)$$

These projections are called the principal components of the original data set.

The PCA has three effects: it orthogonalizes the components of original vectors so that they are uncorrelated with each other; it orders the resulting principal components so that those with the largest variation come first; and it eliminates those components that contribute the least to the variation in the data.

From a geometrical point of view, any covariance matrix is associated to a hyper-ellipsoid in the s dimensional space. PCA corresponds to rotation of coordinates in the way that gives the associated hyper-ellipsoid in its canonical form. The novel coordinate basis is coincident with the hyper-ellipsoid principal axis.

A usual procedure before the feature extraction stage is the scaling of the data. Two main scaling procedures are widely used: zero-centered and autoscaling. Zero-centered data means in our case that each row of data is shifted across the origin, so that the mean of the samples at each test frequency is zero. Autoscaling means to scale each row of data to zero-mean and unitary variance. Only for normally distributed data the covariance matrix completely describes zero-centered data. The assumption of normal distribution is a strong limitations that should be kept in mind when PCA is used.

As alternative to PCA we propose using the histogram-based method.

3.2. Histogram-based technique

Histogram is the basis for an efficient technique to compare analog signals against expected waveforms. The result of processing the data with the aid of histogram is a compressed human readable signature. It is one of the method, recomended by the IEEE 1241 "Standard for Terminology and Test Methods for Analog-to-Digital Converters", using for determination of the converter nonlinearities.

The contribution of this paper is idea of using histogram as the feature extraction method for diagnostic data.

A histogram can be generated from the samples of frequency magnitude or phase responses of the CUT, under the desired conditions of stimulus. It organizes measurement data by dividing magnitude or phase range into K intervals. The number K is called the histogram size, the width of interval is called the histogram bin width. The histogram (Fig. 2a) is formed by simply counting the number of times, which any sample of the response appears within each interval.

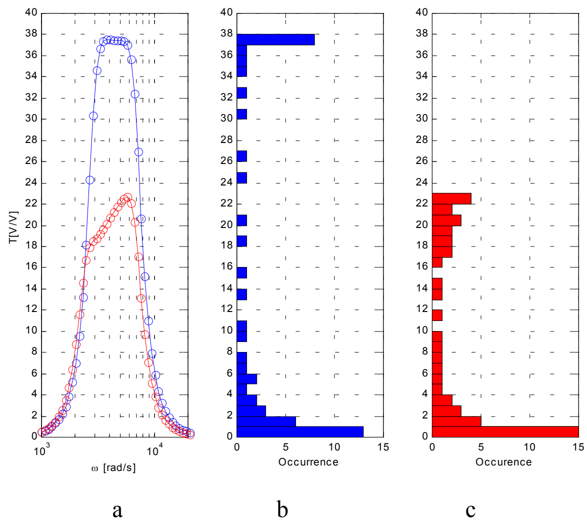

Fig. 2. Transformation of the CUT frequency responses into histograms; a) Bode plots for the healthy circuit and a faulty one, b) histogram for the healthy circuit (template), c) histogram for the faulty circuit.

The acquired histogram can be analysed by comparing with the expected histogram. The results of processing the histogram for faulty circuit (Fig. 2c) against a template histogram (Fig. 2b) is a difference histogram employed as a signature of fault (Fig. 3). The template histogram can be obtained from simulation or by the reference circuit. The signature shows the local distortions caused by faults and provides compressed information useful for diagnosis.

It is worth to notice that histogram-based method is very economical. The size of the signature is much smaller than that of the histogram, which is much smaller than that of the original response. The amount of data that needs to be stored and processed is much smaller than that needed by other methods of feature extraction.

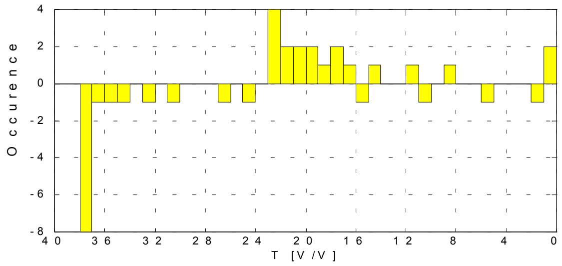

Fig. 3. Difference histogram as a signature of fault

For example, the signature processed from acquired histogram and its template (Fig. 3) may require only a few dozens bytes of data for store.

4. TRAINING AND TESTING OF THE ANN CLASSIFIERS

The 6-th order Deliyannis - Friend filter, shown in Fig. 4, was used as a circuit under test. The circuit is stagger - tuned bandpass filter with Butterworh response.

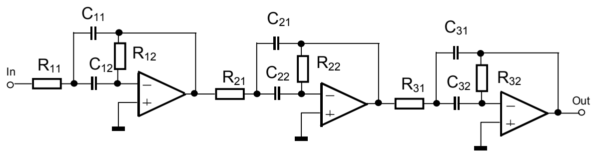

Fig. 4. The circuit under test

Neural networks are trained to classify CUT responses under varying faulty and fault-free conditions, using a set of patterns corresponding to all possible fault classes. During training we repeatedly apply a set of input vectors to the network. The number *r* of input elements of an ANN corresponds to the elements of the training vector, while the number of the output elements is given by the number of fault classes. The classes are coded using a "1-out-of-n" code. With each input training pattern $\boldsymbol{x}_i$ the output pattern $\boldsymbol{y}_i$ is associated, that is defined as follows: $y_i(k)=0$ if fault *k* occurs, and $y_i(k)=1$ if *k* fault does not occur.

One epoch of training is defined as a single presentation of all vectors to the network. The network is then updated according to the results of all those presentations. Training occurs until a maximum number of epochs occurs (ME), the performance goal is met (G), or any other stopping criteria is met.

4.1. Training set design

It is possible to introduce, one by one, all single faults into the CUT and then acquire the corresponding faulty circuit response. This procedure is not practical, thus we have used a higher level abstract behavioral model of the CUT to collect the responses by simulation in Matlab environment. The number of 50 test frequencies were used for each response. It was assumed that all passive elements (12 ones) could be faulty. The single fault model was used. The faulty class responses were generated by assigning element value equal to nominal value ± 50% (open and short circuits). For the sake of simplicity such faults are named R+, C+ or R-, C- respectively. For each fault of interest, families of "faulty" responses were generated by Monte Carlo method (Fig. 5). The 50 Monte Carlo runs were performed for each fault class to build the training set, and the other 50 were used to build the testing set. Totally, there were 1250 signatures generated for training, and 1250 for testing.

The training patterns were constructed from the faulty circuit responses using two described above feature extraction techniques. The dimension of the signatures were reduced from 100 to 5 by means of the PCA, and to 44 by means of the HIST.

Three types of the ANN's have been considered for the experimentation.

4.2. Madaline ANN

As the first, simple single layer network with linear transfer functions (MADALINE) was trained. The design of a single-layer linear network was constrained completely by the diagnostic problem. For the HIST extraction method the number of ANN inputs was determined by 44-elements signature vectors and the number of neurons in the layer was determined by number of fault classes (25). For the PCA extraction method the linear network had one layer of 25 neurons connected to 5 inputs. The least mean square error (LMS) algorithm was used to adjust the weights and biases of the networks so as to minimize the mean square error

$$mse = \frac{1}{Q}\sum_{i=1}^{Q}\left(t(i) - a(i)\right)^2 , \qquad (3)$$

where: *Q* is the number of training patterns, *t* is a target output and *a* is a network output.

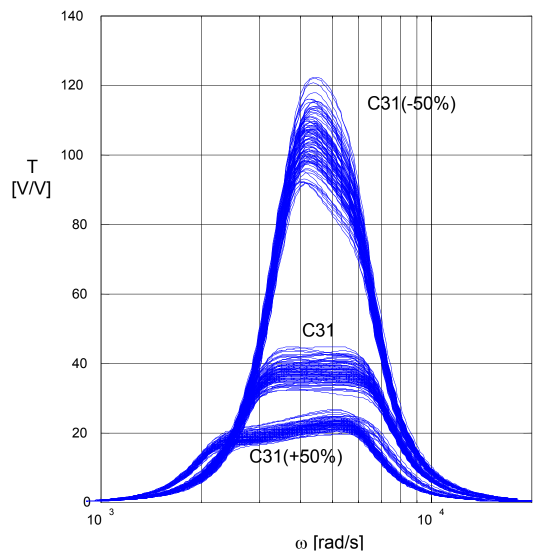

Fig. 5. Families of the responses generated by Monte Carlo method

The results of MADALINE network training and testing are outlined in Table 1. Fig. 6 presents the dependence of the average squared error between the network outputs and the target outputs on the number of epochs.

TABLE 1. The results of training and testing of the single layer network with linear transfer function

Feature extraction method	Stopping condition	Training time [s]	Mean square error	Classification error [%]
HIST	ME	516	14E-3	4,6
PCA	ME	264	30E-3	43,6

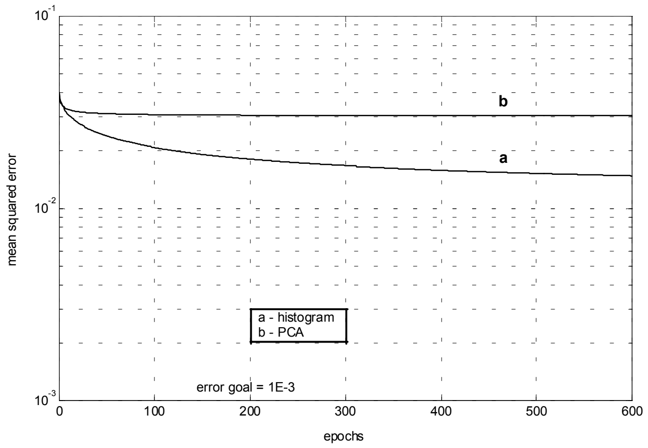

Fig. 6. The dependence of the mean square error on the number of epochs, obtained during training of the MADALINE network

4.3. Neural network with sigmoid activation function

As the second, a two layer ANN with sigmoid activation functions in the hidden layer was chosen. In the network each input node is connected to a hidden layer node and each hidden node is connected to an output node in a similar fashion. The resilient backpropagation (RPROP) training algorithm was used. The RPROP is the simple training algorithm with fast convergence and minimal storage requirements. It is known as the fastest algorithm on pattern recognition problems. For the histogram extraction method the ANN had 44 input, 34 hidden, and 25 output nodes. For the PCA extraction method the network had 5 input, 12 hidden, and 25 output nodes. The results of the sigmoid neural network training and testing are outlined in Table 2. This yields 100 % proper classification for both feature extraction methods. Fig. 7 presents the dependence of the mean square error on the number of epochs, obtained during testing of the sigmoid network.

TABLE 2. The results of training and testing of the neural network with sigmoid activation function

Feature extraction method	Stopping condition	Training speed [epochs/s]	Classification error [%]
HIST	G	0,246	0
PCA	G	0,504	0

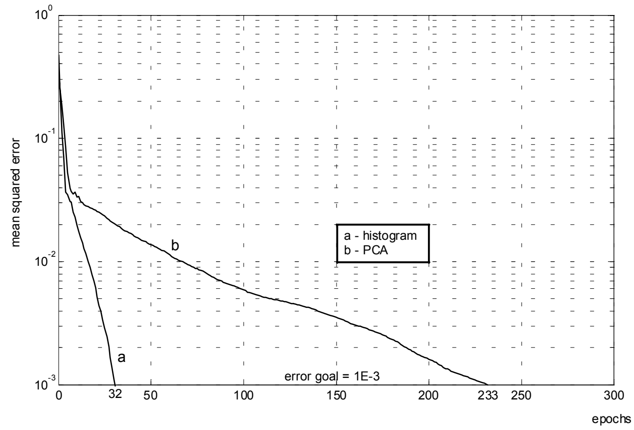

Fig. 7. The dependence of the mean square error on the number of epochs, obtained during training of the sigmoid network

4.4. Radial basis function network

Finally, the radial basis function network (RBFN) with the nonlinearity in the hidden layer, represented by Gaussian functions, was trained. Given the input *x,* the activation function $a(x)$ of the hidden units is given by the following equation

$$a(x) = \exp(-\|\boldsymbol{x} - \boldsymbol{w}\|^2 / \sigma^2)\,, \qquad (4)$$

where: vector $\boldsymbol{w}$ represents the position in the input space of the radial basis function, and σ is the corresponding scaling factor that characterizes the area of the activation region.

In the paper, the variant of RBFN called Probabilistic Neural Network (PNN) was chosen because its predestination for classification problems. The PNN consist of two layers: a hidden radial basis layer and an output linear layer of neurons. The first layer computes distances from the input vector to the training input vectors, and produces a vector whose elements indicate how close the input is to a training input. The second layer sums these contributions for each class of inputs to produce at its output a vector of probabilities. Finally, a compete transfer function on the output of the second layer picks the maximum of these probabilities, and produces a 1 for faulty class that has the maximum probability of being faulty, and 0's elsewhere.

TABLE 3. The results of training and testing of the radial basis function network

Feature extraction method	Number of hidden neurons	Spread of radial basis function	PNN creation time [s]	Classification error [%]	
				Component tolerance	
				R 1% C 2%	R 5% C 5%
HIST	100	0,5	6,2	2,4	30
PCA	100	0,06	6,9	0	11,8

For the signatures obtained by the histogram extraction method the network had 44 input, 100 hidden, and 25 output nodes. For the signatures obtained by the PCA extraction method the network had 5 input, 100 hidden, and 25 output nodes. The results of the radial basis function network training and testing are outlined in Table 3. Fig. 8 and Fig. 9 show the classification errors versus the spread and the hidden nodes number.

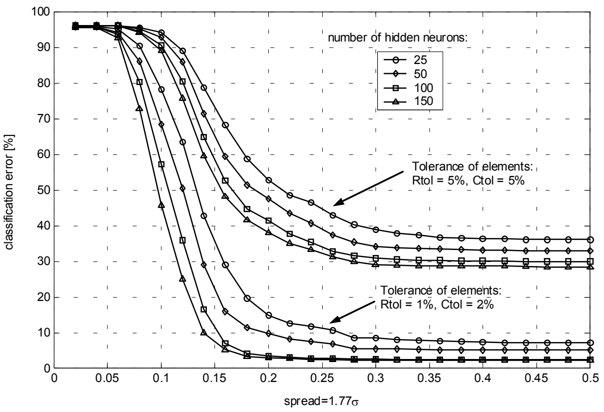

Fig. 8. Classification error versus the radial basis function spread and the hidden nodes number for the case of using the HIST method.

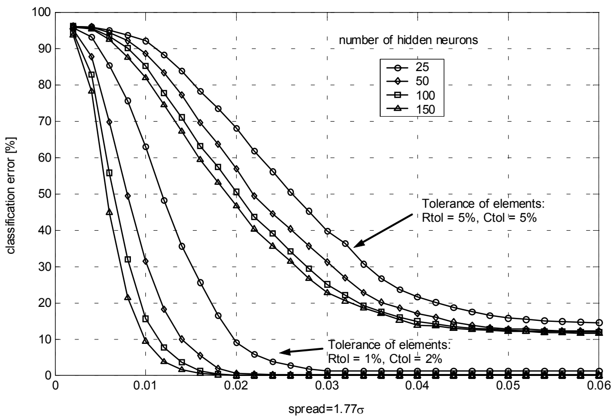

Fig. 9. Classification error versus the radial basis function spread and the hidden nodes number for the case of using the PCA method

The results indicate that the PCA method is more suitable for wider tolerance ranges of the CUT components.

After training, all nets have been used to perform the diagnosis of the real circuit.

5. EXPERIMENTS WITH THE REAL CIRCUIT

During testing of the real CUT, with the aid of diagnostic system, the same feature extraction procedures were used to derive the inputs data for the ANN. The results of diagnosis, related to the CUT shown in Fig. 4, with the aid of two feature extraction methods and three different ANN's classifiers, are outlined in Table 4.

There are 25 single faults classes to consider on the CUT. The empty field in the table means correct diagnosis. The symbol of faulty element in the field means not correctly diagnosed fault.

TABLE 4. Results of diagnosis of the real circuit under test with the aid of different ANN's classifiers

No.	Fault	Madaline		Sigmoid		RBFN	
		HIST	PCA	HIST	PCA	HIST	PCA
1	Fault free		R12+				
2	R11-						
3	R12-		C12-				
4	R21-						
5	R22-						
6	R31-						
7	R32-						
8	R11+		C11+	C11+			
9	R12+						
10	R21+	C21+		C21+			
11	R22+		C22+		C22+		
12	R31+	C31+				C31+	C31+
13	R32+		C32+				
14	C11-		R11-				
15	C12-						
16	C21-		R21-				
17	C22-		R22-				
18	C31-		R31-				
19	C32-						
20	C11+	R11+					
21	C12+		R12+				
22	C21+		R21+				
23	C22+						
24	C31+		R31+				
25	C32+	R32+					

For example, in the case of using histogram-based feature extraction technique, the RBFN has been able to correctly classify 23 faults and fault free condition. Only one fault (R31+) leads to incorrect diagnosis (C31+).

6. CONCLUSIONS

We have compared the results obtained by diagnostic system equipped with two different feature extraction techniques: histogram-based and PCA. A comparison of the classification capabilities of the three ANN's, implemented in the system, versus both techniques has been presented. Histogram-based technique appears to be more effective in improvement of the classifier performance than PCA when using with single layer ANN, and gives the comparable results as PCA when using with a two layer ANN with sigmoid activation functions. It should be noted that the main feature of the histogram-based method is its simplicity and small computational cost. It is extremely easy to implement, but the dimensionality of the data cannot be so greatly reduced as with the aid of PCA.

In this paper histogram generation was performed in software, but it can be easy performed in hardware. Therefore, the histogram approach moves the diagnosis of analog circuits closer to the goal of the ANN-based build-in self-tester (ANNBIST). The histogram-based technique is applicable to a wide range of diagnostic problems.

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