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Fault location and identification in the RIAA equalizer based on the frequency analysis

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***Abstract* – The paper presents the approach to diagnose the RIAA equalizer, which is widely used in the high quality audio industry during the music recording. As the circuit is discrete, it is possible to select the partially accessible nodes for response measurement, therefore analysis of their usefulness for the fault location and identification. The cumulative power of the response at each node was used as the source of diagnostic information. Three classifiers (i.e. decision tree, multilayered perceptron and the gaussian Naïve Bayes Classifier) have been used to identify the faults. Conclusions from the experiments show that it is possible to diagnose the audio circuit using the minimal information.**

***Keywords* – RIAA equalizer, fault identification and location, artificial intelligence**

I. INTRODUCTION

Despite the advancement in digital technologies, analog electronics is still in use, preferred in specific applications. The important one is the audio technology, where traditional, vacuum tubes or bipolar transistors provide desired quality of sound and operation of the devices such as amplifiers or correctors [1]. Such solutions are expensive (each element must be of high quality, i.e. low tolerance), which makes their diagnostics critical, as it is hardly practical (due to high costs) to replace the broken circuit with the new, correctly operating one [2]. Therefore the source of the problem should be identified and processed.

Modern diagnostic approaches rely on the Artificial Intelligence (AI), due to their high accuracy and ability to extract relevant information from the available data. This allows for the semi-automated procedures during the fault detection and location. The selected and optimized AI-based classifiers may be used to point at the faulty element, processing features of the signal responses generated after exciting the circuit with the excitation at the accessible (input) node. The classification accuracy depends on knowledge extracted from the circuit model simulations. The important part of the classifier application is its optimization, which is usually implemented in the offline mode [3]. The particular hyperparameters depend on the selected algorithm and require repeated training-testing cycles for their different values (such as number of neurons inside the layer or the maximal depth of the tree).

The aim of the following paper is to present the diagnostic analysis of the RIAA corrector used during the high quality audio recording. Three AI-based classifiers, i.e. decision tree (DT), multilayered perceptron (MLP) and Naïve Bayes Classifier (NBC) were used to locate and identify parametric faults. They operate on the simple set of features extracted from the frequency characteristics of the response signals measured at partially accessible nodes. Two tasks, i.e. fault location and fault identification were considered.

The content of the paper is as follows. In Section II the analyzed circuit is described. Section III covers the experimental setup (data set, range of classifiers and their work regime). In Section IV experimental results, covering fault identification and location accuracy, and process of their optimization is presented. The work is concluded with summary and future prospects.

II. SYSTEM UNDER TEST

The presented SUT [4] belongs to the high quality audio devices, used during recording of music media, such as vinyl disks. The process requires constant correction of the frequency characteristics to ensure the appropriate quality for the sophisticated listener. In such scenarios the digital integrated circuits are usually not enough, allowing their discrete analog counterparts to take over. Though such solutions are expensive, they must be used if the sound quality is supposed to meet the audiophile society standards. The structure of the system is presented in Fig. 1, with five partially accessible nodes (i.e. the ones where measurements may be taken) encircled. The node No. 5 is the output one, essential for the audio processing. The circuit is a passive filter, consisting of 12 elements: six resistors (indicated from R_1 to R_6) and six capacitors (indicated from C_1 to C_6).

The structure of the circuit reflects the actual construction requirements. Due to the specific connections between some elements (for instance capacitors C_2 and $C3$, and C_5 and C_6, respectively) might be difficult to distinguish, forming ambiguity groups [5]. This should be visible in the classification results (see Section IV).

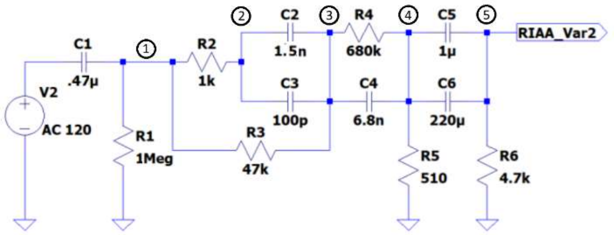

Fig. 1. Topology of the analyzed RIAA corrector

The nominal values of the elements were as follows: C1=0.47uF, C2=1.5nF, C3=100pF, C4=6.8nF, C5=1uF, C6=220uF, R1=1MΩ, R2=1kΩ, R3=47kΩ, R4=680kΩ, R5= 510Ω and R6=4.7kΩ.

Amplitude and phase characteristics are obtained after exciting the SUT with the sinusoidal pattern with the amplitude of 100mV and frequency ranging from 20Hz to 20kHz. Example of the amplitude spectrum is in Fig. 2.

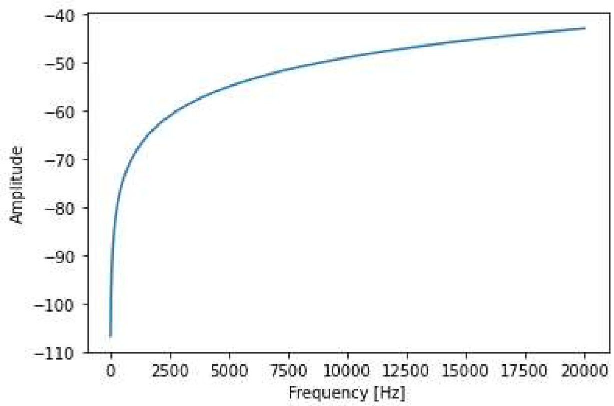

Fig. 2. Amplitude characteristics of the RIAA circuit observed at the output node

III. EXPERIMENTAL SETUP

This section contains description of the framework prepared to analyze the circuit. It uses AI-based algorithms, trained on the available simulation data, and then tested on selected diagnostic cases. All experiments have been conducted in the Python language with the scikit-learn library as the source of the classifiers.

A. Training dataset

The model of the RIAA corrector has been extensively simulated in the LTSpice environment [6]. For each experiment a single parameter (value of resistance or capacitance) was changed beyond the nominal state. The tolerance margins assumed for the model were 10% for each element (which is the low acceptance boundary for the high-quality audio equipment). For each element 20 simulations were conducted. Based on the information about the actual value the fault code was assigned. This way the raw data set R with amplitude and phase samples for 240 simulations was created. Besides the presented experiments, the set is to be used for future research.

The feature dataset D being the base for the presented experiments was constructed using attributes extracted from the spectral characteristics of responses observed at each partially accessible node (indexed 1 to 5 in Fig. 1). The idea was to apply the simplest scheme possible with the minimal number of features for each diagnostics case.

$$a_i = \sum_{j=1}^{N} |f_j|, \quad \text{i=1,…5} \tag{1}$$

where f_j is the amplitude spectrum sample. This way each example is the following vector:

$$\boldsymbol{x}_k = [a_1 \quad \dots \quad a_5 \quad c] \tag{2}$$

with c being the fault code.

B. Applied classifiers

Three classifiers have been selected for the experiment, allowing for comparing their efficiency on the same training data. They were selected due to the different form of stored knowledge, which allows for determining the optimal type of algorithm to tackle the feature vectors. Below their short description is provided.

a. DT is the rule-based approach, building the category separation ability on the tests inside the tree structure. Its advantages include simplicity and legibility for the human operator. The verified hyperparameter was the maximum depth of the tree, influencing the ability to avoid overfitting [7].
b. MLP is the most popular "shallow" type of the feed-forward neural network. Knowledge stored in the arrays of weights connecting neurons between layers I difficult to interpret by the human being. Hyperparameters include the number of layers and the number of neurons in each layer [8].
c. NBC is the simple classifier making decisions based on the probabilities of examples having the particular values of features. Because the latter are continuous, gaussian variant of the algorithm was used (assuming their normal distribution). The distribution smoothing is the hyperparameter here.

The quality of the classifiers was verified using accuracy, being the ratio of correctly identified faults against all present cases.

C. Diagnostic frameworks

Two types of experiments were conducted using the applied classifiers, differing in the fault codes assigned to the examples. In the first one, the aim was the fault location, i.e. finding the faulty element based on the available features. Here the fault code was covered thirteen integers: "0" for the nominal state, and "1" to "12", representing the subsequent elements (i.e. resistors and capacitors, respectively).

The second task was the fault identification, i.e. determining which element is the source of the fault and its actual state (larger than, represented by the negative identifier, and lesser than the nominal - through the positive identifier). This way the number of codes is doubled (i.e. "-12", "-11", …, "11", "12"), with "0", as before, being the nominal state code.

To confirm the efficiency of both approaches and their independence from the available data, cross-validation was used. The repeated stratified hold-out validation procedure was used. In each trial, the dataset was divided into 70% training examples with 30% as the testing ones. Stratification was used to preserve distribution of fault categories in both subsets. Cross-validation was repeated 30 times using different random splits. Results presented in Section IV are then average values with standard deviations representing the dispersion of accuracy around the most common values.

IV. EXPERIMENTAL RESULTS

Three classifiers trained on the subsets of the data set *D* were evaluated regarding their accuracy for two variants of fault categories description (location and identification). Each algorithm has been optimized regarding hyperparameters described in Section III.B. Finally, the minimization of sets of nodes has been performed.

A. Diagnostic accuracy

Compared classifiers show maximum accuracy around 60% in the fault identification task. As the reference level is 2.5 % (assuming each category is equally probable), the result is initially acceptable. The best outcome is reached by DT, with remaining classifiers falling short. Overall results are in Table 1 for identification and in Table 2 for fault location. The worse results for the MLP are probably caused by the insufficient amount of training data, allowing for converging the weight arrays.

Comparison between the performance of fault location and identification shows it is easier to perform classification for more categories. This is because in most cases behavior of the SUT for the element values higher than the nominal one is different than for values below the nominal. When such different examples (for instance, labeled as "-5" and "5") are clustered under a single category, the classifier may not be able to bind them. So, for the larger number of categories the tasks remains easier.

The important aspect is the ability to detect and distinguish between the specific faults, learning which ones are the most difficult to identify. Fig. 3 shows the confusion matrix for the DT classifier in the optimal case. Though most elements are mostly distinguishable. In some cases ambiguity groups remain the problem. For instance, too small values of C_5 capacitor are mistaken for the nominal state (which is not a problem as the Sut behaves as if it was working properly). On the other hand, identifications for capacitors C_2 and $C3$ are intertwined (as mentioned earlier, they are indistinguishable due to the position in the circuit structure). In such a case, the manual diagnosis of both elements would be needed. The confusion matrix confirms the possibility of distinguishing between most of the faults, with the mentioned exceptions.

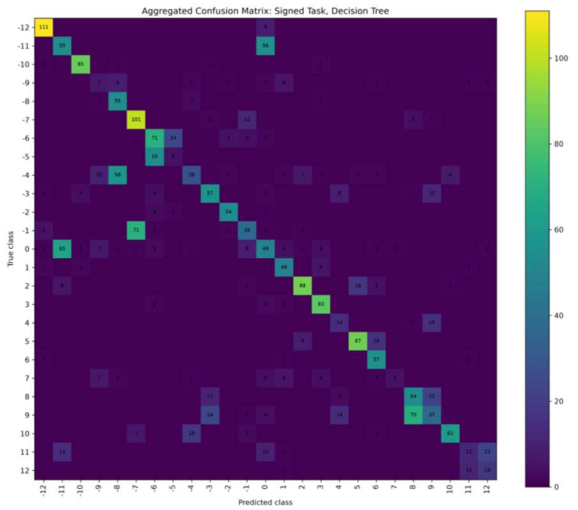

Fig. 3. Confusion matrix for fault identification of the RIAA circuit

Table 1. Optimal average fault identification outcomes for three classifiers

Classifier	Optimal configuration	Accuracy	Standard deviation
DT	Depth = 5	59,35%	3,48%
MLP	Layers: 10:8:6	41,48%	3,72%
NBC	Smoothing=1e-12	53,84%	4,46%

Table 2. Optimal average fault identification outcomes for three classifiers

Classifier	Optimal configuration	Accuracy	Standard deviation
DT	Depth = 10	57,04%	5,71%
MLP	Layers: 20:17	39,44%	4,42%
NBC	Smoothing=1e-12	47,45%	4,55%

B. Classifier optimization

Optimization procedure run on each classifier allowed for obtaining the maximum accuracy. The most critical one was for DT (as it provides the highest accuracy) – see Fig. 4. Here the maximum tree depth equal to 5 allowed to maintain the highest accuracy (Table 1). On the other hand, the gaussian NBC smoothing should be small (Fig. 5).

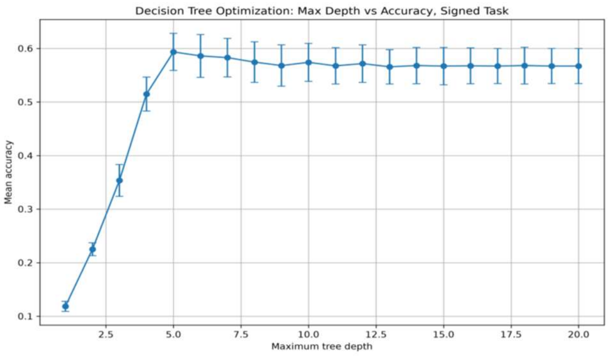

Fig. 4. DT fault identification accuracy as a function of the maximum tree depth

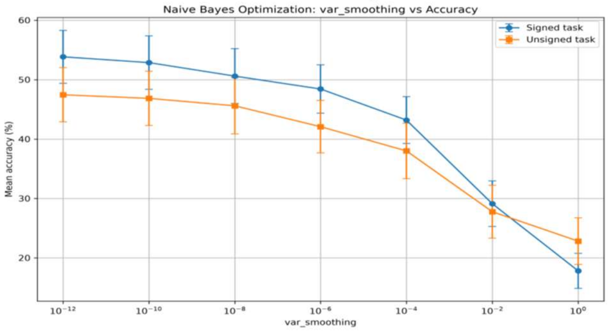

Fig. 5. NBC fault identification and location accuracy as a function of the normal distribution variance smoothing

C. Minimization of nodes

The optimal configuration of DT was used to check possibility of decreasing the number of measurement nodes, maintaining accuracy. The highest score was obtained for data extracted from signals at all five nodes. The procedure to eliminate subsequent nodes (i.e. eliminate attributes from *D*) was applied, with only the fifth (output) one being mandatory. The minimal set was then {5} and maximal one: {1,2,3,4,5}. Only the latter allows for the maximum accuracy, though elimination of some nodes does not degrade the efficiency significantly (Fig. 6). Introducing other attributes from the single measured signal may lead to decreasing number of nodes.

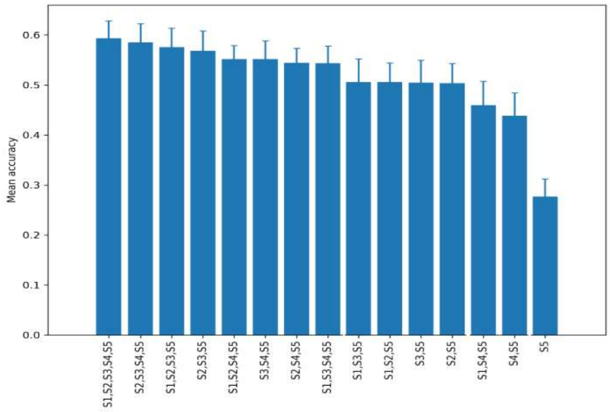

Fig. 6. DT accuracy for different sets of measurement nodes

V. CONCLUSIONS

The presented analysis showed the approach for the diagnostics of the RIAA corrector based on the spectral characteristics of the signals measured on five partially accessible nodes. Three classifiers were applied to process the dataset containing cumulative amplitude spectra. It was established that such minimal information allows for distinguishing between different faults.

Future research should include introduction of other features from the spectral characteristics (such as value and frequency of the maximum peak, or the phase features). Also additional classifiers should be used, specifically the ones tackling uncertainty conditions (such as random forest or the support vector machine). Next, the deep learning may be tried for the scheme, operating directly on the raw measurements [9].

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