SELECTING REUSABLE TEST SIGNALS FOR HEARING INSTRUMENTS WITH A COMBINED DESIGN AND VERIFICATION FLOW

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ABSTRACT

The paper proposes a novel design and verification flow for signal processing systems in hearing instruments, with the purpose of assessing the suitability of test signals for re-use in future versions of a system under development. While a traditional design flow maps idealized functional descriptions of the signal processing algorithms to concrete non-ideal hardware, the new flow maps models of the hardware's typical non-idealities back into the functional description, allowing to study their effect on test signals. The paper uses sample simplified signal processing algorithms for hearing instruments for demonstrating the new modeling approach and uses sample Monte Carlo simulations and sensitivity analysis to show how such models can help determining the suitability of test signals for future variants of the hearing instrument under test.

***Index Terms*—** Test signal, sensitivity analysis

1. INTRODUCTION

During the design of tests for verifying the signal processing performance of a hearing instrument (HI), one important consideration is to keep tests suitable for more than just one version of the HI, particularly because changing and consequently revalidating tests is expensive.

Even though this could be addressed with test signals based on realistic signals, which all versions of a HI are expected to process predictably, realistic signals are not suited well for reaching test coverage. Therefore, synthetic test signals have been proposed (e.g., [1]). These can be designed to drive a HI under test into a well-defined state, but have a dependency on the design of the HI: in general, test signal design has to be re-done occasionally, e.g., when signal processing parameters change during HI development.

Selecting a synthetic test signal with the criterion of decoupling test signals from an individual HI version as much as possible is the goal of this work. This paper proposes to extend a traditional model-based design flow with an activity that targets verification: a novel modeling step produces models for evaluating test signals regarding their suitability for re-use across different products that have different design parameters within a common parameter space. Modeling is based on the assumption that the continuous improvement of HI versions can be described as a parameter change in a functional model that is valid for a set of several HIs.

This paper focuses on the problem of selecting an appropriate test signal from existing candidates rather than on the step of designing test signals to select from. After a brief introduction to the objectives of this work, the paper presents the proposed new design and verification flow and demonstrates its application in an example of HI verification.

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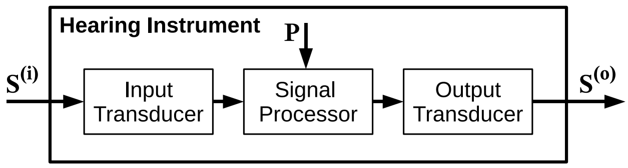

Fig. 1. A simplified model of a hearing instrument.

2. SELECTING REUSABLE TEST SIGNALS

2.1. Definitions

Let V be a vector space and let vector $\mathbf{P} \in V$ be the vector of signal processing parameters of a HI (where vectors are in boldface font). The elements of vector $\mathbf{P}$ are not necessarily run-time parameters of a given HI. They can also be parameters that are fixed at design time, like, e.g., passband and stopband characteristics of filters. Fig. 1 shows a simplified model of a HI whose signal processor is parametrized accordingly and whose input and output are characterized by vectors $\mathbf{S}^{(i)}$ and $\mathbf{S}^{(o)}$ to be explained in the following.

Let $\mathbf{s}^{(\mathbf{i})}$ be a vector of samples of the HI's input signal, like they typically exist in digital test systems for playing stimuli in acoustic tests of HIs via a digital-to-analog converter, and let $\mathbf{s}^{(\mathbf{o})}$ be the corresponding samples of the HI's output signal, e.g., from recording that signal with a digital test system via a measurement microphone and an analog-to-digital converter. Let the number of samples in both vectors be N. Furthermore let $\mathbf{S}^{(\mathbf{i})}$ and $\mathbf{S}^{(\mathbf{o})}$ be the discrete Fourier transform (DFT) of $\mathbf{s}^{(\mathbf{i})}$ and $\mathbf{s}^{(\mathbf{o})}$, respectively, in vector format.

Based on a test vector whose DFT is $\mathbf{S}^{(\mathbf{i},\mathbf{t})}$, the input / output DFT pair $\left(\mathbf{S}^{(\mathbf{i})}, \mathbf{S}^{(\mathbf{o})}\right)$ of the HI can be $\left(\mathbf{S}^{(\mathbf{i},\mathbf{t})}, \mathbf{S}^{(\mathbf{o},\mathbf{exp},\mathbf{P})}\right)$ where $\mathbf{S}^{(\mathbf{o},\mathbf{exp},\mathbf{P})}$ is the DFT of the output one would expect based on an input whose DFT is $\mathbf{S}^{(\mathbf{i},\mathbf{t})}$. $\left(\mathbf{S}^{(\mathbf{i})}, \mathbf{S}^{(\mathbf{o})}\right)$ can also be $\left(\mathbf{S}^{(\mathbf{i},\mathbf{t})}, \mathbf{S}^{(\mathbf{o},\mathbf{obs})}\right)$, where $\mathbf{S}^{(\mathbf{o},\mathbf{obs})}$ is the output DFT that is observed in an experiment with the system under test in which the DFT of the input is $\mathbf{S}^{(\mathbf{i},\mathbf{t})}$. The *test* of the HI for a given parameter vector $\mathbf{P}$ shall then denote the step of carrying out this experiment and determining the deviation $\mathbf{\Delta H}$ between the resulting expected transfer characteristic of the system and the observed one. Via a formula for ΔH_n, the element number n of vector $\mathbf{\Delta H}$, this vector can be defined as a function of parameters and signal DFTs as follows:

$$\Delta H_n\Big(\mathbf{P}, \mathbf{S}^{(\mathbf{i},\mathbf{t})}, \mathbf{S}^{(\mathbf{o},\mathbf{obs})}\Big) = \left|\frac{\mathbf{S}_n^{(\mathbf{o},\mathbf{obs})}}{\mathbf{S}_n^{(\mathbf{i},\mathbf{t})}}\right| - \left|\frac{\mathbf{S}_n^{(\mathbf{o},\mathbf{exp},\mathbf{P})}}{\mathbf{S}_n^{(\mathbf{i},\mathbf{t})}}\right| \quad (1)$$

2.2. Problem statement

Let V_{scope} be a set of different versions of vector $\mathbf{P}$, defined as $V_{scope} = \{\mathbf{P}|\mathbf{P} \in V \wedge \mathbf{P} \text{ is a likely parametrization}\}$, where a *likely parametrization* is one that might be used in a future version of the HI. Then the problem to be solved by an ideal *test design* would be: find one test signal of DFT $\mathbf{S}^{(\mathbf{i},\mathbf{t})}$ from several candidates that are all known to work with one parametrization of the system, such that the following condition holds for the test of an error-free HI with that test signal:

$$\forall_{n\in\{1,2,\ldots,N\},\mathbf{P}\in V_{scope}} : \left|\Delta H_n\left(\mathbf{P}, \mathbf{S}^{(\mathbf{i},\mathbf{t})}, \mathbf{S}^{(\mathbf{o},\mathbf{obs})}\right)\right| \leq \Delta H_{max} \quad (2)$$

Here, ΔH_{max} is the maximum tolerable deviation of the HI's measured frequency response from its nominally expected shape in the test of an error-free HI.

2.3. Current scope

The current scope is limited to selecting test signals that are likely to provide low values of $|\Delta H_n|$ for likely parametrizations of the system, rather than finding signals based on a given ΔH_{max}. This means: an assessment of eq. 2 is needed after test signal selection in order to either validate the test signal or start a new iteration of test signal design.

3. PROPOSED DESIGN AND VERIFICATION FLOW

3.1. Description

This paper is based on a traditional design flow for integrated systems from [2], which separately defines abstract models of system functionality on the one hand, and the mapping of functions to concrete components of the system's microarchitecture as well as the resulting implementation of the system on the other hand. In fig. 2, the elements (a), (b) and (c) represent the corresponding design flow that is taken from [2].

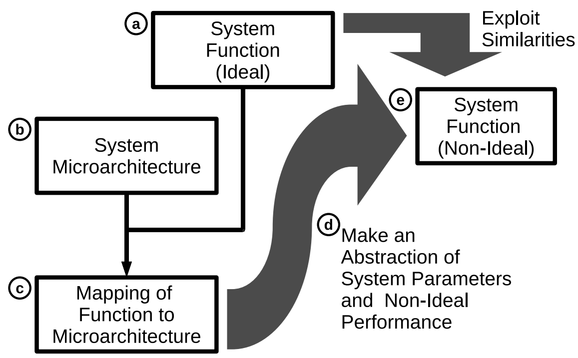

Fig. 2. The basis of the combined design & verification flow: A typical design flow (a to c) based on [2] is extended (d, e).

The mapping introduces non-idealities. For example, leakage effects occur if filtering functionality is mapped on an FIR coprocessor core. These non-idealities, together with the functionality of the system according to element (a) in fig. 2, represent the system characteristics that are relevant for the processing of test signals. In order to produce a model that simplifies the system by reducing it to these aspects, two new parts of the flow are proposed here, as a preparation for evaluating test signals regarding their suitability for reuse:

- Make an abstraction (fig. 2d): Typical parameters and non-idealities of the given system components are identified and described in an abstract way. The abstraction should reduce the number of parameters that are needed to configure the model. For example, a filter should not be represented by its zeros and poles, but by a simplified version of its passband / stopband characteristic, as it will be exemplified further below. Non-idealities have to be accounted for, because they can have an influence on the suitability of test signals for driving the system into a desired state.

- Make a functional system model based on the abstraction (fig. 2e): A functional simulation model of the system is built, taking into the account the abstract system description from above. The functional model is potentially quite similar to the one that was used for the traditional design flow (fig. 2a). Therefore, it is expected that the new model can be established with similar model elements as the one according to fig. 2a, thus exploiting the similarity to reduce modeling effort.

The described flow according to fig. 2 is not yet explicitly related to verification. An additional step, the assessment of test signals during a simulation of the system based on the model according to fig. 2e, addresses verification and thus turns the flow into a combined design and verification flow.

Since the abstraction implies loss of precision compared to reality, the model has to be a *worst case model*, meaning that for a given test signal, eq. 2 should be fulfilled in reality

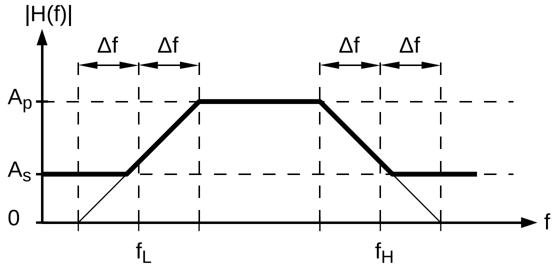

Fig. 3. Abstraction of non-ideal bandpass filter magnitude.

at least in the cases that are predicted from simulations with the model. Based on this prerequisite, a simple criterion on the abstraction step is proposed here: if the system output of a simulation with the abstract model is $\mathbf{S}^{(\mathbf{o,sim})}$ and the output from the real-world situation behind the simulation is $\mathbf{S}^{(\mathbf{o,real})}$, then the following condition should hold:

$$\forall_{n\in\{1,2,\ldots,N\},\mathbf{P}\in V_{scope}}: \left|\Delta H_n\Big(\mathbf{P},\mathbf{S}^{(\mathbf{i,t})},\mathbf{S}^{(\mathbf{o,real})}\Big)\right| \le \left|\Delta H_n\Big(\mathbf{P},\mathbf{S}^{(\mathbf{i,t})},\mathbf{S}^{(\mathbf{o,sim})}\Big)\right| \quad (3)$$

3.2. Example

The example of a bandpass filter may explain the novel abstraction steps: In a functional model of a new signal processing system according to fig. 2a, the designer would describe a bandpass filters by its upper and lower crossover frequency. If the model according to fig. 2a was to be explored by simulation, a filter of relatively high order would be chosen in order not have filter non-idealities spoil the assessment of the signal processing algorithm per se. According to fig. 2c, the bandpass filter would then be mapped to a DSP core or a filter core on the target platform for implementation. In this step, constraints on clock cycles or chip area or the given coprocessor performance of the target platform may dictate a considerably lower order of the bandpass filter, resulting in a non-ideal frequency response with limited slope steepness and with passband ripple as well as stopband ripple.

An abstraction of this non-ideal frequency response is given in fig. 3: the crossover frequencies for use in a filter bank are f_L and f_H, respectively. The parameter Δf can be varied to set the slope steepness, parameter A_s controls non-ideal stopband attenuation as an abstraction of stopband ripple, and the parameter A_p can be varied to change the passband gain, for modeling passband ripple.

With the symbol $\delta(t)$ for the Dirac impulse, one possible impulse response $h(t)$ of the abstract bandpass filter is:

$$h(t) = A_s\cdot\delta(t) + 2(A_p - A_s)\cdot\left(f_H - f_L - 2\cdot\Delta f\cdot\frac{A_s}{A_p}\right) \cdot\cos\left[2\pi\cdot\frac{f_H+f_L}{2}\cdot t\right]\cdot sinc\left[\left(2-2\cdot\frac{A_s}{A_p}\right)\cdot\Delta f\cdot t\right] \cdot sinc\left[\left(f_H - f_L - 2\cdot\Delta f\cdot\frac{A_s}{A_p}\right)\cdot t\right] \quad (4)$$

Under the assumption that the whole system according to fig. 1 is a bandpass filter only, it can easily be verified that the condition of eq. 3 holds for the above abstraction of the bandpass filter with $\mathbf{P} = (A_p, A_s, f_L, f_H, \Delta f)^T$, because worst case elements of $\mathbf{\Delta H}$ can be obtained by mis-tuning A_p and A_s according to the worst passband and stopband ripple, respectively, and by accounting for finite slope steepness of the filters with an appropriate choice of Δf.

4. EXPERIMENTS

4.1. Methods

4.1.1. Monte Carlo experiments

To find out the influences of further development of the system on the suitability of test signals, simulations with different parameter vectors $\mathbf{P}$ had to be performed. While a complete assessment of test signals in the sense of section 2.2 would require a simulation over the complete parameter space V_{scope} and would lack practicality, the approach chosen here is one that is found in the practical assessment of parameter influences on models [3]: *Monte Carlo experiments* can be used to assess the sensitivity of system variables on other system variables. They are experiments based on simulations of the system of interest that are parametrized with random numbers and allow the experimenter to study the system in simulation, without incurring the time and cost of its actual physical construction [4]. Each random generator is calibrated to approximate the statistical distribution of the system parameter that is parametrized with its random numbers.

4.1.2. Sensitivity Analysis

Unlike other common methods of sensitivity analysis, *global sensitivity analysis* [3] does not evaluate partial derivatives of system equations, but it analyzes how parameter variations based on the probability distributions of system parameters influence the performance of the system, based on Monte Carlo experiments. For a system that relates an output variable Y with an input parameter vector $\mathbf{X}$, Saltelli et al. [3] define the *first-order sensitivity index* S_i that is a quantitative sensitivity indicator expressing the sensitivity of Y to changes of element number i of vector $\mathbf{X}$:

$$S_i = \frac{var_{X_i}\{E_{X\sim i}\{Y|X_i\}\}}{var\{Y\}} \quad (5)$$

Here, $var_{X_i}\{...\}$ is the variance over the term in curly braces, in the situation in which element number i of vector $\mathbf{X}$ varies according to its probability distribution, whereas $E_{X\sim i}\{...\}$ is the expected value of the left term in curly brackets obtained when all elements but i vary accordingly and the right term in curly braces stays constant. The higher the value of S_i the higher is the sensitivity of the variable Y to changes of vector element X_i.

In practice, an approximation $S_i^{\sim}$ of the first-order sensitivity index can be obtained by analyzing the results for Y from Monte Carlo experiments, in dependency of parameter number i, and computing discrete $E_{X\sim i}\{Y|X_i\}$ over finite value ranges of X_i rather than for distinct values. This has been proposed by [3], interpreting values of Y that result from a value range of X_i as a "slice" of a scatter plot that plots Y vs. X_i based on results of Monte Carlo experiments.

4.2. Modeled system under test

The system under test was a fictitious HI, containing only a modulation-based noise reduction system. Since performance measurements of noise reduction systems are available from prior work ([1, 5]), no new measurements had to be made. It was thus sufficient to establish a simulation model of the system according to fig. 2d/e. This was done, resulting in a discrete time model that is valid for periodic input signals of a fixed period length. The noise reduction itself was modeled in the form that is given in [6] with several changes due to the necessity of making an abstraction and of having it match the system of interest.

Noise reduction subbands were chosen like in the specification of the HI used in [5], regarding the number of subband and their split frequencies. In consequence, a filter bank instead of the three dedicated filters from [6] had to be designed. The subband split filters in the filter bank were modeled as discrete-time FIR filter representations of the filter abstraction that is given in fig. 3 and eq. 4, using a Hamming window. A filter realization with 512 taps was chosen to ensure that deviations of the frequency response from the one shown in fig. 3 stayed negligible. Passband and stopband attenuation of the filter were set with constant values $A_p = 1$ and $A_s = 0.005$; the parameter Δf was left variable for simulating potential future design changes of the HI.

The modulation estimator was simplified: the maximum and minimum of the signal envelope within one period of the simulated input signal yielded the modulation estimate m, by subtracting the results of the minimum operation from the one of the maximum operation, on the decibel scale.

The envelope estimator in the modulation estimator was implemented according to [7] with empirically determined settings of the attack parameter $\alpha = 0.97$ and release parameter $\beta = 0.99$ (where α and β are defined in [7]).

The attenuation a in dB was computed from the modulation estimate m via $a = \max\left[\min\left(20 - m/\nu, 10\right), 0\right]$, where ν was a noise sensitivity parameter that was left variable.

Note that the described model of the noise reduction system is highly simplified, meaning that a satisfactory noise reduction system for use in a real HI could not be built from the description given by the model. However, for the purpose of obtaining an abstraction of the system within the verification flow proposed in this paper, the model was assumed to have an appropriate level of simplification.

Param.	Description	Mean	Standard deviation
ν	Noise sensitivity of the noise reduction system.	1.25	0.15
Δf	Filter slope parameter as to fig. 3.	100 Hz	30 Hz

Table 1. Parameters of the example system.

4.3. Procedure

The problem of test signal selection according to section 2.3 was interpreted as a problem of sensitivity analysis by defining that among the evaluated signal candidates, the selected one should yield least sensitivity regarding the system output's deviation from nominal with an error-free system during variations of parameters that are variable within the space V_{scope}. The measure of sensitivity was the first-order sensitivity index, as ideally given by eq. 5.

The test signal candidates were the two different alternatives presented in [5], i.e. periodic signals with defined modulation in different subbands, based on multi-sines for one candidate of the test signal, and based on a special binary signal, a *discrete-interval binary signal* [8] on the other hand.

A computer program for simulating tests with the system under test was implemented by means of simulation scripts for the MATLAB® technical computing environment. The vector of variable parameters was $\mathbf{P} = (\nu, \Delta f)^T$. The simulation program was used to perform 1000 Monte Carlo experiments per test signal, where the elements of vector $\mathbf{P}$ were varied on the basis of uniform distributions whose mean and standard deviation are listed in table 1. The variation of these parameters was supposed to model possible changes during a potential further development of the modeled system. The noise reduction transfer function for each simulation experiment was computed according to [1].

For performing sensitivity analysis, the $\mathbf{X}$ vector according to eq. 5 was set equal to the $\mathbf{P}$ vector from above, and Y was chosen to be the Euclidean norm of vector $\mathbf{\Delta H}\left(\mathbf{P}, \mathbf{S^{(i,t)}}, \mathbf{S^{(o,sim)}}\right)$ as a measure of the error made during the test with an error-free system, where $\mathbf{S^{(i,t)}}$ was the test signal under evaluation. The resulting equation for computing the sensitivity index is given below.

$$S_i = \frac{var_{P_i}\left\{E_{P\sim i}\left\{\left\|\mathbf{\Delta H}\left(\mathbf{P}, \mathbf{S^{(i,t)}}, \mathbf{S^{(o,sim)}}\right)\right\|_2 \middle| P_i\right\}\right\}}{var\left\{\left\|\mathbf{\Delta H}\left(\mathbf{P}, \mathbf{S^{(i,t)}}, \mathbf{S^{(o,sim)}}\right)\right\|_2\right\}} \quad (6)$$

Here, the samples of $\mathbf{P}$ to be used in computing variances and expected values were those ones that resulted from the Monte Carlo experiments. The approximation $S_i^{\sim}$ of the first-order sensitivity index according to section 4.1.2 was computed for each varied parameter per test signal, as a measure of how sensitive the errors occurring in the simulated tests with an error-free system were to changing the respective parameter in the simulated system under test.

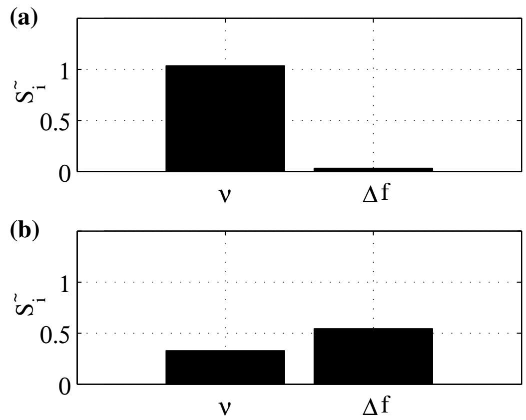

Fig. 4. Approximated first-order sensitivity indexes:
(a) test signal based on discrete-interval binary signals
(b) test signal based on multi-sines

4.4. Results

Fig. 4 shows the results of the Monte Carlo experiments, i.e. the approximated sensitivity indexes. The higher the bar in the bar chart, the higher is the sensitivity of the test design to changes in the parameter that is stated below the bar.

5. DISCUSSION

An interpretation of the result shown in fig. 4a can be that a test of the noise reduction system with a test signal based on discrete-interval binary signals may be more sensitive to changes in noise sensitivity in the noise reduction system under test than to changes of its filter slopes. This is consistent with an observation from [1], where experiments with noise reduction systems of different modulation sensitivity were reported to show that discrete-interval binary sequences produced side effects for systems with high noise sensitivity only, when used as a basis for test signal design.

The result shown in fig. 4b could in turn indicate that test signals based on multi-sines may not be suited if the filter slope of bandsplit filters in the noise reduction system under test is expected to vary in future products. A possible explanation for the dependency of quality of multi-sine based tests on filter slopes is given in [1], where results of experiments with different multi-sine-based test signals are explained by non-idealities of band split filters in the system under test.

As a result, one would thus choose signals based on discrete-interval binary sequences for testing noise reduction systems with low sensitivity to unmodulated noise and a high likelihood that the slopes of bandsplit filters rather than the noise sensitivity would change during the further improvement of the system. On the contrary, one would choose signals based on multi-sines for systems with a high likelihood of changes regarding the noise sensitivity. In many cases, one would have to look for a third test signal candidate with a low sensitivity to both parameters. E.g., [1], presents variant of the multi-sine-based stimulus that was reported here, with less sensitivity to variations of filter ideality.

6. CONCLUSION

The presented design and verification flow was exemplified with a simplified HI that only contained a noise reduction system. Monte-Carlo simulations and computation of an approximated first order sensitivity index allowed for predicting how sensitive two candidates of system tests would react to changes in some of the system's parameters. The predictions were consistent with findings in prior work.

Yet, it was not possible to show how the strict problem according to section 2.2 can be solved. Furthermore, the shown example only had two variable parameters, which is an unrealistically simple situation. It was also not yet investigated how the certainty of the predictions depends on the number of Monte Carlo experiments and on the choice of the parameters' statistical distributions.

Further work should address how the obtained models can be used to make more certain prediction of test signal suitability with systems having a considerable higher number of parameters. It should address the potential for application of the proposed flow not only for noise reduction systems, because it may e.g. be suitable also for sound classification systems and for transient noise suppression systems.

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