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Model-based Hearing Diagnosis of Middle Ear Condition Using Inverse Fuzzy Arithmetic and Artificial Neuronal Network

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Abstract

Due to the large interindividual variances and the poor optical accessibility of the ear, the specificity of hearing diagnostics today is severely restricted to a certain clinical picture and quantitative assessment. Often only a yes or no decision is possible, which depends strongly on the subjective assessment of the ENT physician. A novel approach, in which objectively obtainable, non-invasive audiometric measurements are evaluated using a numerical middle ear model, makes it possible to make the hidden middle ear properties visible and quantifiable. The central topic of this paper is a novel parameter identification algorithm that combines inverse fuzzy arithmetic with an artificial neural network in order to achieve a coherent diagnostic overall picture in the comparison of model and measurement. Its usage is shown at a pathological pattern called malleus fixation where the upper ligament of the malleus is pathologically stiffened.

Keywords: middle-ear model, model-based ENT diagnostic, wideband tympanometry, fuzzy arithmetic, artificial neural network

1 Problem

Current clinical diagnostics of the hearing capability of a patient is based on a number of different subjective and objective audiometric tests. Subjective tests require attention and the active reaction of the patient to sound and comprise amongst others pure-tone audiometry and speech audiometry. These tests are fairly accurate, but test the complete hearing path, consisting of three stages: middle ear, inner ear, and neural path. Comparing with bone-conduction, a less accurate diagnosis of the air conduction (i.e. middle-ear) is possible. Current clinical practice cannot distinguish, with any degree of certainty, the multiple pathologies that produce conductive hearing loss in patients with an intact tympanic membrane and a well-aerated middle ear without exploratory surgery [1]. Further, subjective tests are impossible to perform in new-borns or difficult and with clearly reduced accuracy to perform in young children, but also in elderly or seriously ill adults.

None of the today clinically used objective audiometric methods provides a frequency-specific loss of a particular stage of the hearing path (i.e. middle ear/inner ear/neural path) in isolation, and only a minority provide a direct, quantitative measure of a frequency-specific loss at all. Rather, most methods provide a norm range of performance against which the test data are compared, and are given in a measure, which cannot be directly converted to a loss figure. Thus, today, the medical specialist is concluding his diagnosis of the state of the hearing path based on a weighted judgement of the typically five to eight different tests. In addition, he has to draw his conclusion keeping in mind the highly diverse limitations of these techniques. Thus the most desirable and concise description would be a frequency-, level-, and stage-specific loss (or gain) figure.

Impedance audiometry is today the most important objective audiometric diagnostic test. In the past decades its performance and validity range was improved by expanding the frequency range from single tones (226/1000 Hz) to wideband measurements (0.2 – 8 kHz) and analysing impedance data in amplitude and phase, rather than just comparing the impedance (compliance) curve of a single tone with its normal range. The benefit of wideband impedance measurements was shown by several authors who observed distinctive frequency-specific patterns for various middle ear pathologies like otosclerosis, ossicular discontinuity, tympanic membrane perforation and otitis media with effusion ([2], [1]) in comparison to the statistical range of normal hearing. However, so far, the effects of middle ear pathologies on wideband impedance measurements are not completely understood and there are neither simple objective criteria to be able to distinguish between several pathologies with any certainty, nor a quantitative estimation of middle-ear transmission loss to the inner ear.

Lately, the classical tympanometry and wideband impedance measurements were combined in the so called wideband impedance tympanometry (WBT), which essentially measures the wideband acoustic input impedance of the hearing path (typically 0.2 – 8 kHz) under different static ear canal pressures (-300 – 200 daPa). WBT is not only very practical and efficient, since tympanometry and impedance measurements are performed simultaneously, but also allows to evaluate the wideband impedance at balanced static middle ear pressure (tympanic peak pressure), which leads to better repeatability and comparability of wideband impedance measurements between individuals. Since the static ear canal pressure is varied, the nonlinear stiffening properties of the middle ear (mainly tympanic membrane and joints) are reflected in a systematic way in the measurements which can potentially be used for differential diagnosis as shown in [1] with regard to disarticulation of the incudo-stapedial joint and malleus fixation. Clear advantage that WBT shares with classical tympanometry is stage specificity for the middle ear. Compared to laser vibrometry, WBT has the clear advantage of economic instrumentation and a quick and easy measurement procedure.

Several numerical middle ear models are known in hearing research today, but they do not yet contribute to individual, patient-specific quantitative diagnostics. The basic structure of the middle ear and the function of the individual middle ear elements (eardrum, bones, ligaments, joints, etc.) are the same for all people and can be represented in a mathematical model with the help of the finite element method in a firmly defined structure. The individually different properties of the individual anatomical middle ear structures, such as ligament stiffness or inertia of the ossicles, can be described in the model by variable numerical parameters. Their selection determines the individually different response of the ear model to a specific excitation signal. Our finite element (FE) model of the ear presented in [3], [4] and [5] is based on micro-CT data and static as well as dynamic measurements.

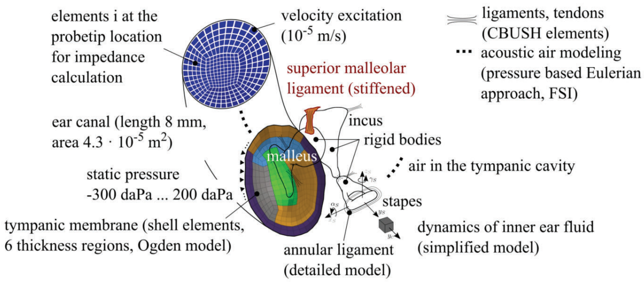

Figure 1: *FE model of the middle ear used for the simulation of wideband tympanometry and the model-based diagnosis. The model has an acoustic ear canal, a tympanic cavity, an elastic tympanic membrane, and an ossicular chain. Furthermore, the superior malleolar ligament is highlighted, since it is later stiffened to simulate a pathological pattern called malleus fixation to demonstrate the model-based diagnostic approach.*

Focusing on the middle ear, this paper suggests a novel approach to arrive at a frequency-, level- and stage-specific diagnosis of middle ear hearing loss by the evaluation of the most advanced audiometric measurement technique, the wideband impedance tympanometry (WBT), within the scope of an identification process to determine individual middle ear model parameters using inverse fuzzy-arithmetic and artificial neural network. By comparing the model response with objective diagnostic measurements on a patient, a patient-specific parameter set can be determined using parameter identification algorithms. Since the model parameters are directly linked to anatomy-specific physical properties of the ear, this process quantifies the individual middle ear properties hidden behind the eardrum and assigns them to a localizable specific anatomical property. For the parameter identification, it is advantageous to have as much information as possible about the individual ear, which is why the model-based approach benefits from the use of extensive objective measurement data and combines these into a coherent overall picture. The diagnosis can finally be made based on objectively determined, quantified and locally resolved middle ear properties, which promises a considerably higher specificity for common middle ear diseases compared to the conventional diagnostic approach [6]. The question therefore arises whether it is possible to move from the conventional comparison with standard curves to an objective, quantitative and personalized diagnosis of the middle ear by means of a model-based evaluation of objective measurements.

The complexity of the anatomical structure requires a large number of model parameters, which cannot be unambiguously determined today by the mere application of standard parameter identification algorithms. The paper therefore suggests a hybrid solution strategy combining inverse fuzzy arithmetic and artificial neural network. Its usage is shown at a pathological case called malleus fixation where the superior ligament of the malleus is pathologically stiffened due to an ossification process.

2 Material and Methods

In the following firstly the FE model of the ear and the parameter identification procedure including the inverse fuzzy arithmetic approach and the artificial neural network are presented.

2.1 FE Model of the Human Middle Ear

The FE model of the middle ear is shown in Fig. 1. The air in the ear canal and tympanic cavity is modelled with acoustic finite elements. The aditus ad antrum and the air in the mastoid are modelled as a one mass oscillator, which reproduces the oscillating air between the tympanic cavity and the mastoid, and corresponds to a Helmholtz resonator phenomenon. The fluid-structural coupling between the tympanic membrane (TM) and the adjacent air is implemented using a pressure-based Eulerian approach. The ear canal wall is considered rigid by fixing all degrees of freedom. The ossicles are modelled as rigid bodies and characterized by their mass and inertia, because the ossicles deformation can be neglected up to 10 kHz. Whereas malleus and incus have all 6 degrees of freedom, the stapes is further constrained, allowing only a translational piston motion along the y-axis and two rotational (rocking) motions around the x- and z-axis of the stapes coordinate system. The ligaments, tendons and joints are represented by passive spatial spring-damper elements.

The geometry of the tympanic membrane is reconstructed from micro-CT data. Six regions are defined with constant thickness, which were derived from the characteristic relative thickness distribution. When preloaded, the TM stiffens due to large deformation and material nonlinearity. In the model, shell elements are used and the nonlinear material characteristics are described by a stress-dependent tangent modulus $d\sigma/d\epsilon = a\sigma + b$ with the stiffening characteristic a and the Young's modulus b in the unloaded case. In the model, a is derived from uniaxial tensile tests of TM stripes and b is chosen according to measurements of the middle ear's transfer behaviour.

The annular ligament is modelled according to measurements from [4], who derived the stiffness characteristics of the annular ligament on human temporal bones. Therefore, the stapes annular ligament system was isolated by dissecting the chain. At several points on the stapes footplate the applied forces were increased step by step and the spatial displacement of the footplate was measured using a laser vibrometer. The derived inhomogeneous stiffness distribution of the annular ligament was modelled by eight translational and two rotational progressive nonlinear springs, distributed along the circumference of the stapes footplate.

We simulated a complete calcification of the superior malleolar ligament (SML) as a test case for the model-based diagnosis, where the ligament is grown together with the tympanum. In that case, the stiffening effect is high, because rotational degrees of freedom are severely affected. Therefore, in our simulation, we used a stiffening factor of 10000 for the SML for all translational and rotational stiffness values. In comparison, the normal stiffness value for the SML in its principal direction in our model is 700 N/m, which corresponds to a Young's Modulus of 9 MPa. The simulation of WBT is done in two steps. First a non-linear large deformation static analysis is conducted with pressure levels from -300 daPa to 200 daPa. The static pressure is applied in steps of 50 daPa on the tympanic membrane. Second, based on the static analysis a dynamic frequency response analysis is carried out in the frequency range from 0.2 to 8 kHz, with a uniform velocity excitation in the ear canal of 10^{-5} m/s at a distance of 8 mm from the umbo, see [8]. The energy absorbance (EA) is calculated from the velocity excitation and the resulting pressure averaged over the excitation plane. This is done for every static ear canal pressure level to calculate the 3D WBT diagrams.

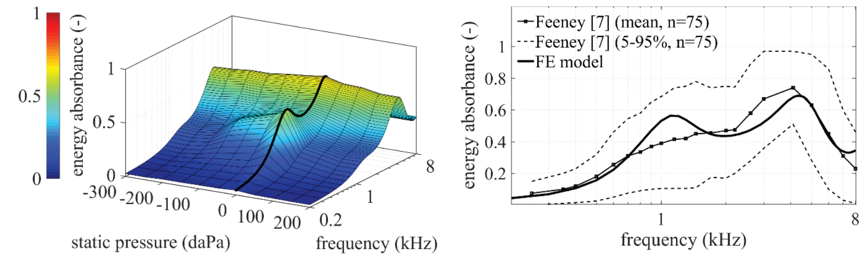

***Figure 2**: Simulated EA-pressure-frequency curve of a mean normal ear (left). The black line shows EA at static pressure of 0 daPa and is compared in the right figure to published measurement data on normal hearing patients.*

2.2 Inverse Fuzzy Arithmetic

The parameter identification by means of inverse fuzzy arithmetic represents an optimization problem with the model parameters as design variables. Its goal is to minimize the deviation between the values predicted by the model and the measured values. During modeling, assumptions and simplifications lead to errors that cause uncertainties in the statements made by the model. On the measurement side, the uncertainties arise mainly from the complexity and poor accessibility of the middle ear, which do not allow all necessary model states to be observed.

Both together lead to an ambiguity or uncertainty in the parameter identification, since different parameterizations lead to similarly plausible model responses. The application of inverse fuzzy arithmetic now makes it possible to quantify the uncertainties in the identification of the model parameters using fuzzy numbers. The parameter set with the smallest overall uncertainty in the identified parameters (smallest parameter scatter) is selected as the most plausible parameterization. In contrast to purely stochastic methods, fuzzy arithmetic allows a simple integration of expert knowledge, which is indispensable for the definition of parameter clusters. In addition, measurement uncertainties can be taken into account without having to have precise knowledge of the stochastic distribution functions.

The propagation of uncertainties described by fuzzy sets is based on fuzzy arithmetic which is fundamentally based on the extension principle by Zadeh [9]. The direct problem is described by a mapping of a fuzzy input set of the uncertain model parameters to a fuzzy valued output set. The transformation method introduced by [10] and used in this study is a numerical approximation of the extension principle and prevents the overestimation of uncertainties in the fuzzy output. The transformation method uses a so called α-cut approach, where the fuzzy sets are subdivided by α-cuts into several subsets with equally spaced membership levels and transformed into arrays that define possible parameter combinations. The evaluation may be done with crisp numbers and therefore the transformation can be applied on black-box models. Afterwards the generated output arrays are retransformed and the fuzzy-valued output is recomposed. A detailed description of this procedure can be found in [10]. This approach further enables sensitivity studies through an efficient calculation of influence measures of the uncertain model parameters on the system response. The inverse problem is to identify the input fuzzy sets $\mathbf{x}$ that generate a prescribed output. To reach a conservative coverage of the output, the uncertainty of the estimated sets needs to be maximized and the distance to the output set using the estimated input sets needs to be minimized. Using the α-cut approach, the input-output mapping is approximated by a linear mapping $\mathbf{F}$ and by introducing the tolerances $\mathbf{m}$ of the prescribed output, the quadratic program for the identification problem can be described as

$$\min_{\mathbf{x}} \ \mathbf{x}^{\mathrm{T}}\mathbf{F}^{\mathrm{T}}\mathbf{F}\mathbf{x} - 2\,\mathbf{m}^{\mathrm{T}}\mathbf{F}\mathbf{x} \quad \text{subject to } \ \mathbf{F}\mathbf{x} \leq \mathbf{m}.$$

2.3 Artificial Neural Network (ANN)

However, the inverse fuzzy approach needs to solve the direct problem first and therefore requires an initial guess for the fuzzy sets in advance, which in turn may influence the result. Furthermore, a costly optimization problem needs to be solved and this approach is additionally restricted to the transformation method. In the context of this paper, a novel concept is investigated, where an artificial neural network (ANN) determines the initial parameter set for the direct problem. These networks are capable to recognize patterns or characteristics based on graphical data like WBT contour plots. Apart from using standard multilayer perceptrons with two hidden layers, convolutional networks will be used. Convolutional networks are well known from deep learning and offer the advantage that preprocessing of the data is not necessary as the network itself can extract meaningful features from the data. Therefore, a two-step algorithm is proposed: The ANN assigns the individual ear to a rough class of middle ear characteristics associated with a certain initial parameter set by an initial assessment of the diagnostic measurements. Based on that, an inverse fuzzy arithmetic is used to make a fine adjustment and to determine the most plausible parameter set. The training and cross validation for the ANN is done with virtual patient WBT measurements obtained by simulations with the ear model. Interindividual variations are considered by a random selection of the parameter set from a predefined parameter domain. The performance of the ANN is tested at three categories "normal hearing", "pathology I: malleus fixation" and "pathology II: disarticulation".

3 Results

Fig. 3 shows three examples of simulated WBT diagrams out of the mentioned three ear categories. The differences between the categories are most evident in the shape of the 3D hill at the first resonance and result from an increased stiffness of the SML for pathology I and a reduced stiffness of the incudo-stapedial joint for pathology II, each by an average factor of 10000. The differences within the categories are due to a superposition of significantly smaller stochastic parameter fluctuations. In this way a total of 100 data sets were randomly generated. In order to classify these data sets we used a four-layer perceptron with resilient backpropagation. The three hidden layers had 50, 50, and 10 neurons. The activation function at the hidden layers was a hyperbolic tangent and at the output layer, consisting of three neurons (one for each class) the softmax function, a smoothed version of the threshold function. The error measure was the cross entropy. The training goal was usually reached in less than 15 iterations. The ANN was trained on 40 randomly selected data sets and was then able to assign the remaining 60 data sets with almost 98% to the correct category. Details about the performance are given in the confusion matrix for the 60 test data sets in Fig. 3.

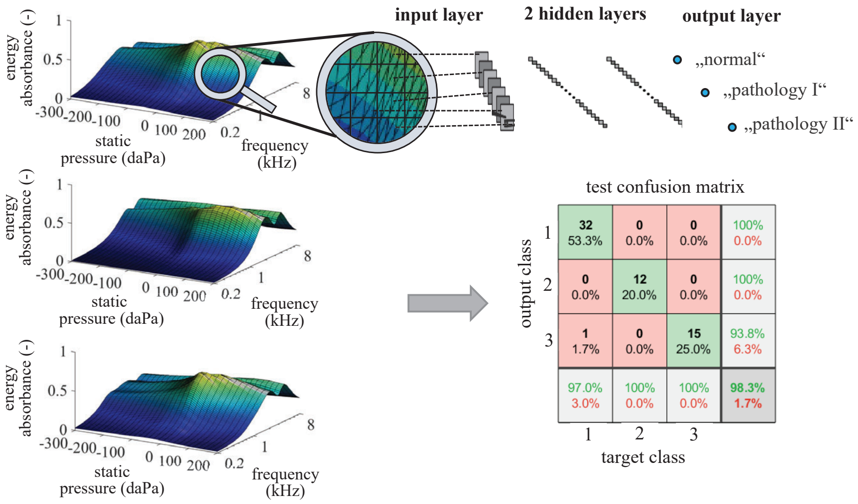

Figure 3: *Simulated WBT 3D-diagrams of a normal ear (top), pathological ear type I (middle) and type II (bottom). Testing on 60 simulated data sets out of the three categories resulted in the shown confusion matrix.*

After the rough classification with the ANN the fine-tuning of the parameters is carried out with inverse fuzzy arithmetic. Exemplarily it was done for the ear class "pathology I", an ossified superior malleolar ligament. Since the fixation of the superior malleolar ligament (SML) was simulated with a stiffening factor of 10000, see section 2.1, the inverse fuzzy arithmetic is supposed to identify a fuzzy set including the nominal parameter value. Fig. 4 shows the membership function of the stiffening factor together with the nominal value. The narrow bound of the fuzzy set in Fig. 4 denotes that the stiffening parameter could be determined with a high degree of confidence. The shape of the identified fuzzy set consists of nested sets and therefore can be asymmetric. The nominal value of the parameter read meets nearly exactly the parameter value for a membership of one from the identified fuzzy set.

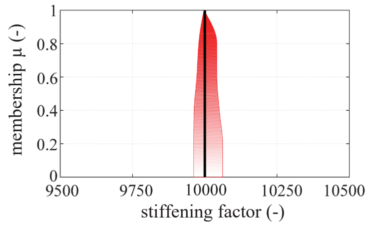

Figure 4: *Stiffening factor of the superior malleolar ligament derived with the FE model and inverse fuzzy. The nominal value is shown by a vertical line.*

4 Discussion

In contrast to the current clinical diagnosis, in which global middle ear characteristics are compared with normal ranges, the new parameter identification algorithm can resolve and quantify middle ear characteristics locally. In clinical practice, this can be used to determine stage-specific hearing loss and localize pathologies to better plan middle ear surgery. In addition, a patient-specific model can be used for a tailored development of prostheses and hearing aids. In order to be suitable for clinical diagnosis, first, the model must be able to describe all anatomical changes through pathologies and inter-individual variations. Secondly, the model parameters need to be sensitive to specific pathological parameter changes to reliably predict them. The cause-effect-relationships between model parameters and ear characteristics can be identified by fuzzy arithmetic, while the inverse fuzzy arithmetic allows us to estimate the most likely parameter set. The reliability of the diagnosis may be valued by the fuzzy approach, as the worst-case intervals of the identified fuzzy numbers and fuzzy output can be used as a measure of the model validity. Furthermore, fuzzy arithmetic is especially suited to dealing with uncertainties introduced by inaccurate (mathematical) modeling due to lack of knowledge, simplification and idealization in modeling. Concerning the initial guess for the parameter set providing a basis for fuzzy arithmetic using ANN, we plan to leave out the detour determining a pathology class to the data set. We want to train a convolutional network for the regression task of delivering directly a parameter set. However, it is only possible to prove the validity of the prediction of model parameters by the parameter identification procedure by measurements on temporal bones. Therefore, laser vibrometer measurements of ossicles motions and WBT measurements should be carried out.

5 Conclusion

In this paper, we have introduced a new model-based approach based on the example of a FE ear model, which was used to simulate the WBT of an ear with malleus fixation. Through this example, we have shown the benefits of a model-based quantitative evaluation. The consideration of uncertainties due to model simplifications and incomplete knowledge of parameter distributions is done using fuzzy arithmetic and the parameter identification, with the help of inverse fuzzy and an artificial neural network. By considering these approaches, our example has given insight into the great potential of the model-based approach in providing us with a more reliable patient-specific quantitative evaluation of WBT measurements that may be extended to other diagnostic methods.

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