Characterizing Tire and Wind Noise using Operational Path Analysis

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Motivation

An interactive driving simulation requires on-demand reproduction of vehicle sound components such as engine, wind and tire noises as separate sound contributions. For realistic sound perception, wind and tire noises are extracted from road measurements. During a coast-down (engine switched off) from maximum vehicle speed to standstill, only a mixture of wind and tire noise can be measured. But separated tire and wind noise can be better modified, evaluated and auralized. Therefore, based on the vehicle interior noise and additional airborne and structure-borne measurements, wind and tire noise shares must be predicted. Two different approaches will be discussed.

Model

Input signals are recorded where the tire noise arises from the contact of the tires with the road surface. For each tire two microphones and a triaxial acceleration sensor are used measuring, respectively, airborne and structure-borne sound, leading to twenty input signals $x_j(t)$ with j=1..20 for the model. The interior noise $y_i(t)$ with i=1..2 is recorded simultaneously by an artificial head for a binaural simulation. The tire noise $s_i(t)$ in the cabin results from twenty transfer paths for each output signal $y_i(t)$. The wind noise $n_i(t)$ can be modelled as an additive uncorrelated noise. In the following, two methods for separating tire and wind noises will be presented and compared. Whereas the **M**ultiple **C**oherence **F**iltering (MCF) [1] relies on a kind of Wiener-Filtering [2] of the mixture (the interior noise), the **O**perational **P**ath **A**nalysis (OPA) [3] consists of determining the filters of the MIMO model and synthesizing the tire sound according to the functional block diagram shown in Figure 1.

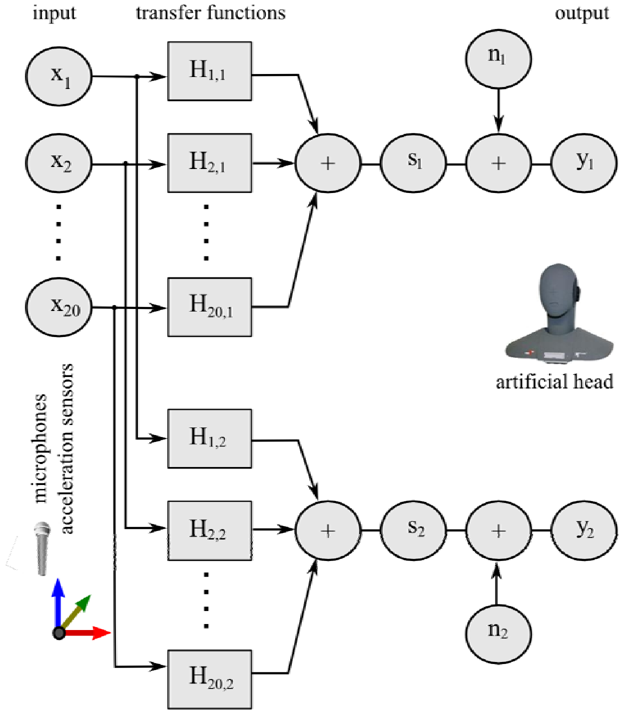

Figure 1: Multiple **I**nput **M**ultiple **O**utput Model

Multiple Coherence Filtering (MCF)

According to the Wiener-Filter theorem the output signals can be filtered achieving an estimation of the tire and wind components. The composition of these components must be stationary. This condition can be fulfilled if small segments of the measurement are separately analyzed assuming stationarity. The left and right ear signals of the artificial head are treated independently. The multiple coherence function between the inputs and the output is used as the transfer function $H_{MCF}(f)$ of a filter creating the tire component based on the vehicle interior noise [4]. The wind noise estimation can be calculated as the difference signal between interior noise and tire noise. The multiple coherence function describes the portion of the output power which can be expressed by the input measurements. In other words it shows the linear dependence between input and output. The multiple coherence function is normalized in order to obtain a number between 0 and 1 for each frequency. A value of 1 means that at this frequency the entire output power is caused by the input. In this case the interior noise consists of tire noise only. In the opposite case, where the multiple coherence function is zero, there is only wind noise.

Operational Path Analysis (OPA)

OPA is an alternative approach based on first filtering the input measurements from the road and then summing the filtered signals. For this synthesis the transfer functions of the model are required. The input and output signals of the system are known, so it is possible to estimate the transfer functions using correlation techniques. This leads to two advantages compared to classical **T**ransfer **P**ath **A**nalysis (TPA) with explicit measurements of transfer functions. First, time-intensive measurements are not needed and second, the system is under working conditions. The correlation-measuring techniques used for OPA have been known for decades, but the computing power of today's computers makes their use practicable. This approach works in the frequency domain by calculating the Short Time Fourier Transform (STFT) of the input and the output signals. The results of this block-based transform are the output quantities $Y_i(f,m)$ i=1,.2 and the input quantities $X_j(f,m)$ j=1..20 with the frequency index f and the block index m=1..M. The matrix notation allows a short and elegant description. For every frequency f the input quantities are combined to the matrix $\mathbf{X}(f)$ containing the values for all input sensors and all blocks

$$\mathbf{X}(f) = \begin{pmatrix} X_1(f,1) & \cdots & X_1(f,M) \\ \cdots & \ddots & \vdots \\ X_{20}(f,1) & \dots & X_{20}(f,M) \end{pmatrix}. \quad (1)$$

For each output microphone signal the values are arranged as a row vector:

$$\mathbf{Y}_i(f) = \begin{pmatrix} Y_i(f,1) & \cdots & Y_i(f,M) \end{pmatrix}. \quad (2)$$

The transfer functions $H_{i,j}(f)$ from input j to output i are also written as row vectors:

$$\mathbf{H}_i(f) = \begin{pmatrix} H_{i,1} & \cdots & H_{i,20} \end{pmatrix}. \quad (3)$$

For a shorter notation the frequency index f and the output sensor index i are discarded in the following. The output **Y** is the sum of the tire noise **S** and the wind noise **N**.

$$\mathbf{Y} = \mathbf{S} + \mathbf{N}. \quad (4)$$

As described in the model the tire noise is a sum of the filtered input signals, so for every frequency the following system of equations is achieved:

$$\mathbf{Y} = \mathbf{H}\mathbf{X} + \mathbf{N}. \quad (5)$$

If there are more transform blocks than input sensors the system of equations is over-determined and a solution in the least square sense

$$\min \left\| \mathbf{Y}\text{-}\mathbf{H}\mathbf{X} \right\|_2, \quad (6)$$

can be calculated using the pseudo-inverse:

$$\mathbf{H} = \mathbf{Y}\mathbf{X}^+. \quad (7)$$

It can be shown that this is identical with estimating transfer functions using correlation methods described in [1]. In matrix notation the input spectral density matrix is

$$\mathbf{G}_{xx} = \tfrac{2}{M \cdot U} \mathbf{X}^* \mathbf{X}^T, \quad (8)$$

where U is the window energy of the STFT. The input/output cross-spectral density matrix can be written as

$$\mathbf{G}_{xy} = \tfrac{2}{M \cdot U} \mathbf{X}^* \mathbf{Y}^T. \quad (9)$$

The transfer functions are calculated with

$$\mathbf{H}^T = \mathbf{G}_{xx}^{-1} \cdot \mathbf{G}_{xy}, \quad (10)$$

and equation (8) and (9) inserted in (10) gives

$$\begin{aligned} \mathbf{H}^T &= \left(\mathbf{X}^*\mathbf{X}^T\right)^{-1} \cdot \mathbf{X}^*\mathbf{Y}^T \\ \mathbf{H} &= \mathbf{Y} \cdot \left(\left(\mathbf{X}^*\mathbf{X}^T\right)^{-1} \cdot \mathbf{X}^*\right)^T \\ \mathbf{H} &= \mathbf{Y} \cdot \mathbf{X}^H \left(\mathbf{X}\mathbf{X}^H\right)^{-1} = \mathbf{Y} \cdot \mathbf{X}^+. \end{aligned} \quad (11)$$

The pseudo-inverse is usually computed by the singular value decomposition, which is numerically more favourable, because the condition of the matrix **X** would be squared with the inversion of $\mathbf{XX}^H$.

After calculating all the transfer functions for all frequencies, the tire noise can be synthesized and the wind noise can be determined as the difference signal between interior noise and tire noise.

Comparison

Both approaches require the same measuring effort. The important difference lies in which signals are processed in order to obtain the tire noise. MCF uses the output signal to estimate both wind and tire noise. Therefore the estimation signals are correlated, although the assumption was made that wind and tire noises are uncorrelated. This leads to an incorrect power estimation of wind and tire noise. Here, the coherence filter function can be expressed by the **P**ower **S**pectral **D**ensity (PSD) of tire and wind noise and the mixture signal

$$H_{MCF}(f) = \frac{G_{SS}(f)}{G_{YY}(f)} = \frac{G_{SS}(f)}{G_{SS}(f) + G_{NN}(f)}. \quad (12)$$

Now the ratio between the estimated and the actual wind noise depends on the power ratio of tire and wind noise.

$$\begin{aligned} \frac{G_{\tilde{N}\tilde{N}}(f)}{G_{NN}(f)} &= \left|1 - H_{MCF}(f)\right|^2 \frac{G_{YY}(f)}{G_{NN}(f)} = \left|1 - \frac{G_{SS}(f)}{G_{YY}(f)}\right|^2 \frac{G_{YY}(f)}{G_{SS}(f)} \\ &= \ldots = \frac{1}{1 + SNR} \qquad SNR = \frac{G_{SS}(f)}{G_{NN}(f)}. \end{aligned} \quad (13)$$

On the same way one can show for the tire noise that

$$\frac{G_{\tilde{S}\tilde{S}}(f)}{G_{SS}(f)} = \frac{1}{1 + \frac{1}{SNR}}. \quad (14)$$

With increasing **S**ignal-to-**N**oise-**R**atio (SNR) the power of the wind noise estimation decreases more and more while the power of the tire noise rises to the actual value. In the opposite case where the SNR is decreasing it is contrariwise. This will be illustrated using the following example: for an arbitrary frequency the PSDs of tire- and wind noise are both supposed to be 20 (mPa)²/Hz. In the case of uncorrelated signals the PSD of the mixture equals the sum of the individual PSDs 20 + 20 = 40 (mPa)²/Hz. The multiple coherence function has a value of 0.5 because half of the energy can be expressed by the tire noise. Filtering the mixture will lead to a PSD of $(0.5)^2 \cdot 40 = 10$ (mPa)²/Hz for both the tire noise estimation and for the correlated difference signal. If the signals are added again the power is still equal to 40 (mPa)²/Hz because the signals are correlated, but the estimated power in this case is only half of the actual value.

On the other hand, OPA filters the input signals in order to estimate the tire noise. This generates uncorrelated estimations with correct power if the assumptions are fulfilled. Theoretically, OPA is the better method. MCF has another advantage: errors in the input signals have no direct influence on the estimated tire noise but only on the multiple coherence function. Therefore this approach may be more dependable than OPA due to fewer artifacts in the auralization.

Examples

A simulation shows the properties of OPA and MCF under different conditions. Only four impulse responses with a length of 1024 samples, calculated from measured data, are used to synthesize the simulated tire noise. The parameter FFT length has an effect on the ratio between estimation and residual signal (Figure 2). A large FFT length should be used under the condition that the STFT calculates enough values for the system of equations (7). In this trivial case there is no wind noise and both approaches show a very good estimation of the averaged spectra (Figure 3). Here a length of 8192 samples and a Hanning window were chosen, so that the residual signal is about 30 dB below the estimation.

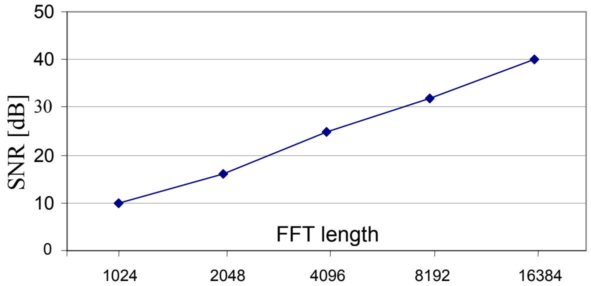

Figure 2: Relation between FFT length and SNR without additional wind noise**.**

Now an artificial wind noise (filtered white noise) is added. Its averaged spectrum is always 10 dB below the tire noise. Figure 4 shows that OPA estimates tire as well as wind noise correctly whereas MCF estimates the dominant tire noise well, but the wind noise with too little level as demonstrated previously. In the opposite case (wind noise always 10 dB above the tire noise) MCF extracts a correct wind noise, but the estimation of the tire noise fails (Figure 5).

OPA handles correlations in the input signals, but correlations in those measurements which are not transferred, like crosstalk between the input sensors, cause errors in the estimated transfer functions. The sum of all paths, here the tire noise, remains correct. In a simulation the input signals were mixed by adding 25% of all other input channels to each input. The output signal was the same as in the previous examples. As shown in Figure 6 the crosstalk has no influence on the estimated tire noise, but in contradiction to the case without crosstalk (Figure 7) the resulting transfer function is incorrect (Figure 8), because the transfer functions are also mixed.

The model does not cover input disturbances, which of course occur in measured data. In order to simulate this, filtered white noise with a SNR of -10 dB was added to each input channel. Now the estimations show errors (Figure 9).

An example using measured data is shown in Figure 10. A luxury car is analyzed for a speed range from 80 to 60 km/h. The vehicle interior sound is dominated by the tire noise which is well-estimated by both approaches. But MCF leads to a wind noise with too little level (incorrect power estimation). Although if the wind noise is combined with the louder tire noise, this problem becomes unimportant due to masking effects. On the other hand, the OPA wind noise prediction is at the correct level and sounds more authentic in informal listening tests.

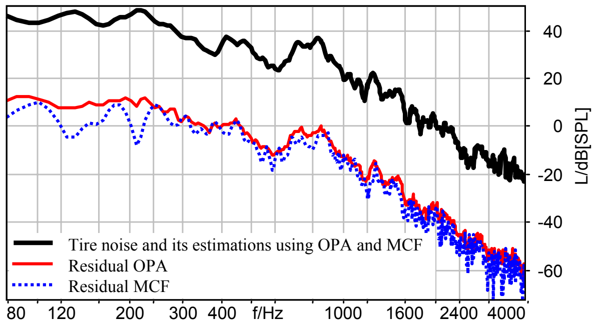

Figure 3: Averaged spectra for the simulation without wind noise.

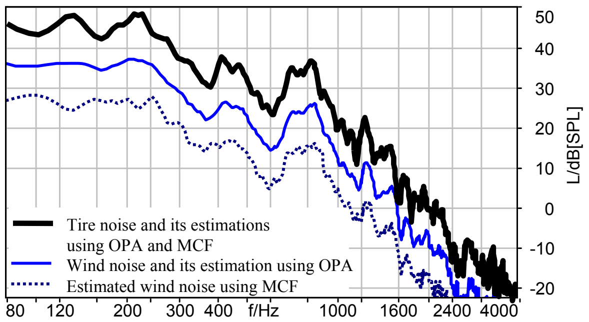

Figure 4: Averaged spectra for the simulation with -10 dB wind noise. In the context of drawing accuracy the tire noise and its estimations from OPA and MCF are equal. The wind noise estimation using OPA corresponds to the wind noise, but the MCF estimation shows too little level.

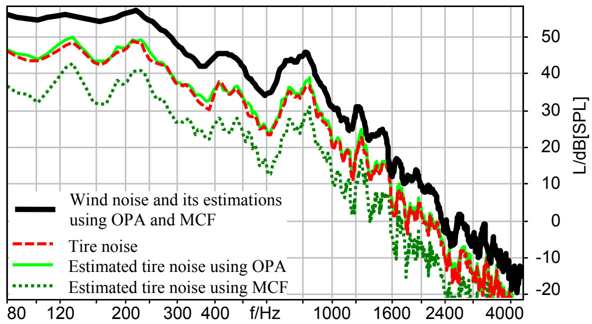

Figure 5: Averaged spectra for the simulation with +10 dB wind noise. The tire estimation from OPA corresponds to the tire noise, but the estimation from MCF shows too little level. In the context of drawing accuracy the wind noise and its estimations from OPA and MCF are equal.

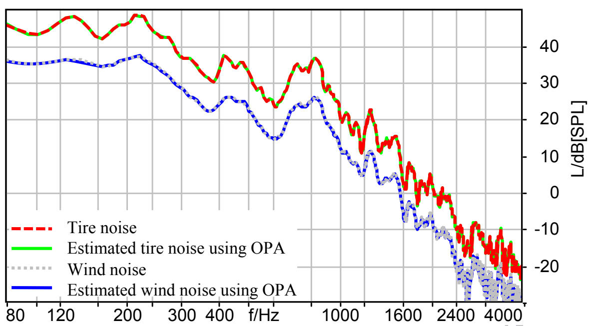

Figure 6: Averaged spectrum for the simulation with crosstalk. Although there is crosstalk in the measured input signals which is not transferred to the vehicle interior, the estimated tire noise is correct.

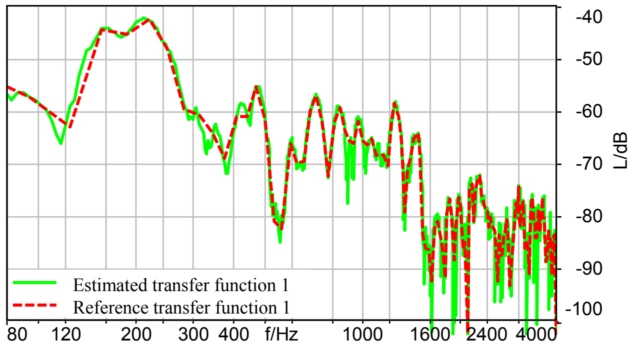

Figure 7: Estimated transfer function 1 vs. reference used in the simulation.

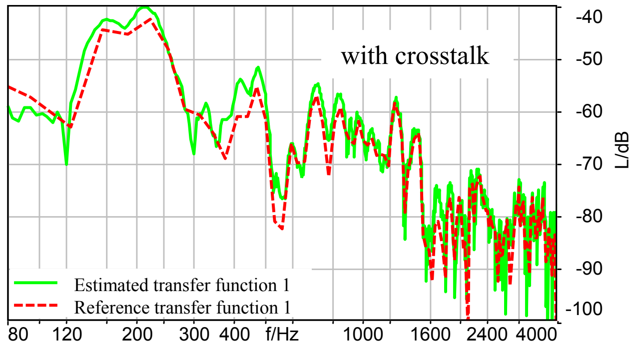

Figure 8: Crosstalk in the measurements, which is not transferred, causes errors in the estimated transfer functions.

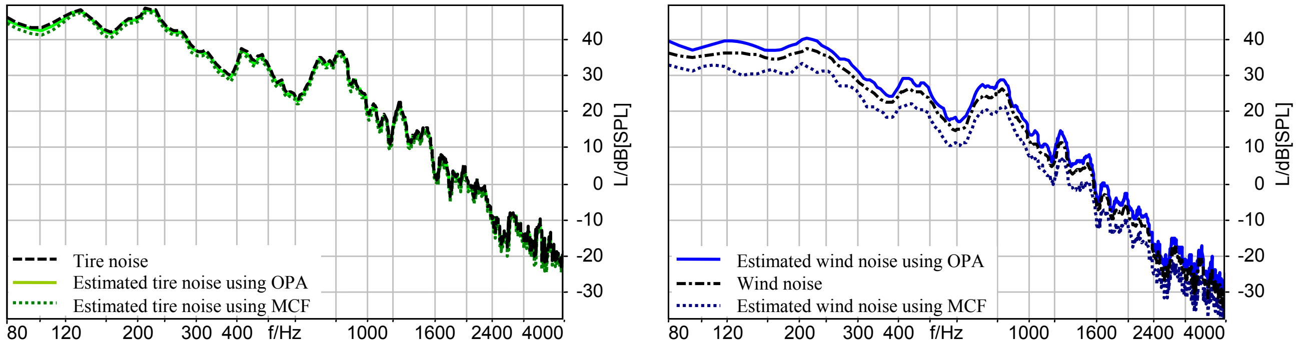

Figure 9: Averaged spectra for the simulation with -10 dB input noise and -10 dB wind noise. The tire noise estimations are not as good as in Figure 4. The wind noise estimations are more affected by the input noise; estimated levels using OPA are too high.

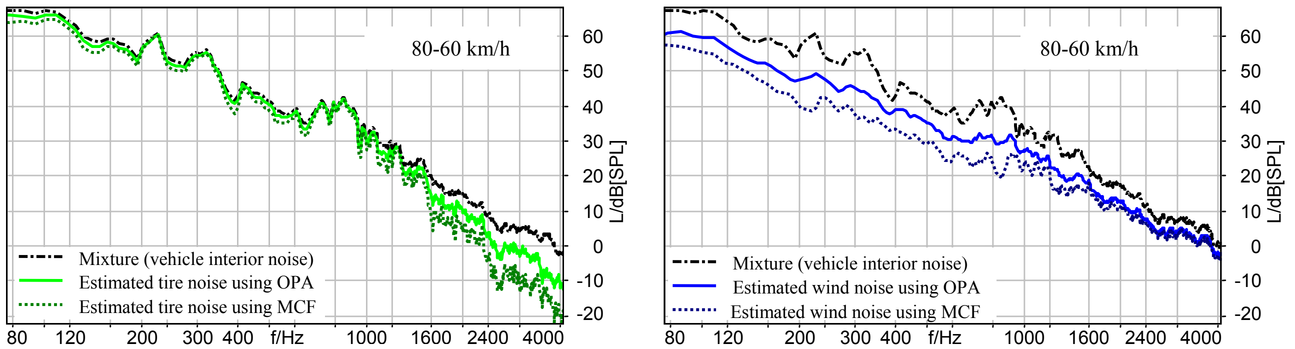

Figure 10: Averaged spectra for the analysis of measured data taken from a coast-down from 80 to 60 km/h. The tire noise estimations using OPA and MCF are shown on the left and the wind noise estimations on the right.

Conclusion and Outlook

Operational Path Analysis allows a better characterization of tire and wind noise than Multiple Coherence Filtering. Further improvements of OPA could be a treatment or at least an automatic recognition of disturbances in the input signals and the reduction of crosstalk at the sensor side. This would enhance the quality of the estimated transfer functions.

If OPA is compared to classical TPA, it must be noted that individual path contributions may be incorrect, e.g. in the case of an unconsidered path, although the sum of all paths shows a good synthesis (especially if the missing path is highly correlated to the others) [5]. Here, this limitation has no effect because only the complete tire noise is of interest. However, a contribution analysis of individual tires yielded similar results for OPA and classical TPA.

References

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