BALANCING ON THE ROAD

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SUMMARY

Modern passenger cars are equipped with measurement technology to control the function of engine and different safety systems. In addition, the requirement for improved ride comfort is growing which means that the vibrations of the vehicle has to be minimized. One source of vibrations are unbalanced rotating parts of the vehicle due to wheels and drive shafts. To compensate such unbalances the present technology is based on measurements off the road and the dynamic behaviour of the vehicle system is not taken into account. This paper presents a method based on the parameter identification of a multibody system model of the vehicle to determine the value and angular location of compensation weights for the wheels to achieve an overall compensation of harmonically excited vibrations on the road. Thus, the complete dynamic vehicle system driving on its rolling wheels is taken into account.

1. INTRODUCTION

The harmonic excitation of vehicle vibrations is due to unbalances of wheels and drive shafts as well as geometrical nonuniformity and radial stiffness variations of tires. While the unbalance of a wheel can be reduced by balancing off the road, the other sources of excitation cannot be controlled so well. Therefore an overall compensation of harmonically excited vehicle vibrations in a certain speed domain system is the adequate approach.

An overall compensation of vibrations is possible only if the vehicle travels on its rolling wheels. However, in this case the measured signals depend on the dynamic behaviour of the total vehicle system. For that reason the presented balancing technique requires simultaneously both, the identification of the mechanical parameters of the transfer function, e. g. the tire stiffness, and the evaluation of the parameters of the compensation weights, i. e. its values and positions at the wheels.

Describing the excitation by the rough road surface as a coloured, ergodic, Gaußian stochastic process and applying the state equations to represent mathematically the mechanical model of the vehicle, one obtains an algebraic Ljapunov matrix equation as a basis for parameter identification by calculating the second moments of the solution process of a steady–state vehicle motion. The covariance analysis for system identification was developed subject to stochastic excitations by Weber and Schiehlen [1] and was presented in detail by. Kallenbach [2], [3].

The covariance analysis has been extended for the compensation of harmonic excitations of a vehicle [4]. For the presented identification of unbalances the symbolically generating of equations of motion is more appropriate than a numerical algorithm, because knowledge about the structure of the multibody system can be taken into account. The symbolical equations of motion can be derived by hand or with the help of suitable computer programs. General purpose vehicle system dynamics software based on multibody formalisms was reviewed by Kortüm and Schiehlen [5] and Kortüm and Sharp [6].

During the theoretical development of the presented method it was assumed that the mathematical vehicle model and the computer generated road profile are realistic. Thus, the acceleration signals were obtained by numerical integration of the nonautonomous system including a linear shape filter for the generation of a realistic noise excitation from white noise excitation. The equations of motion were generated symbolically by the NEWEUL program package, Kreuzer and Leister [7]. The simulations were executed by the NEWSIM program, Leister [8].

With regard to the balancing problem stated, the covariance analysis is well qualified. Starting with symbolically generated equations of motion and their transformation to an observer normal form, the identification of mechanical parameters can be achieved by measuring accelerations exclusively. Differentiating or integrating of measured signals is not needed.

As mentioned, the covariance analysis for the identification of the parameters was extended to deterministic excitation. Thus, beside the cross covariance matrices between the output signals $\mathbf{y}$ of a linear filter and the measured accelerations $\ddot{\mathbf{z}}$, and between $\mathbf{y}$ and the excitation $\mathbf{u}$ by the road profile at each wheel, respectively, the cross covariance matrix between $\mathbf{y}$ and the harmonic excitation $\mathbf{d}$ is needed, too, i. e. $\mathbf{C}_{y\ddot{z}}, \mathbf{C}_{yu}$ and $\mathbf{C}_{yd}$. If the excitation $\mathbf{u}$ by the road is unknown, the matrix $\mathbf{C}_{yu}$ is also unknown. In this case one has to consider measurements at different speeds to maintain the identificability. Then, the knowledge on the quadratic increase of the acceleration amplitude due to excitation by unbalanced masses can be taken into account. However, this additional information has to be transformed to the covariances, too.

To verify the theoretical results in engineering applications, a test vehicle is designed. The paper presents schematically how data acquisition and processing is performed on the test vehicle.

2. IDENTIFICATION OF UNBALANCES

2.1. Modeling of Vehicle

The presented method for identification of unbalances with the covariance analysis is based on stationary small motions around the equilibrium position of the vehicle. In addition, the vehicle is described as a multibody system and the Newton–Euler equations were derived relative to the center of mass of each body. Therefore, the linearized equations of motion of the vehicle read

$$\mathbf{M}\ddot{\mathbf{z}}(t) + \mathbf{P}\dot{\mathbf{z}}(t) + \mathbf{Q}\mathbf{z}(t) = \mathbf{g}(t) + \mathbf{s}(t) \tag{1}$$

see Müller and Schiehlen [9]. Here $\mathbf{z}(t)$ is the fx1-vector of generalized coordinates, $\mathbf{M}$ is the symmetric, positive definite fxf-inertia matrix, $\mathbf{P}$ is the fxf-matrix of velocity dependent forces and $\mathbf{Q}$ the fxf-matrix of position dependent forces. The fx1-vectors $\mathbf{g}(t)$ and $\mathbf{s}(t)$ consist of the harmonic and stochastic excitation forces, respectively.

Unbalance forces can be modeled as single particles revoluting on a certain radius with the rotor frequency within a plane normal to the axis of rotation. At each unbalanced rotor there can be one or more unbalance planes. If there is only one unbalance plane one speaks of static unbalance, otherwise of dynamic unbalance.

If the vehicle travels on its rolling wheels beside the harmonic excitation due to unbalances there appear other periodic forces due to geometrical nonuniformity and radial stiffness variations of tires. All deterministic vibration sources are combined in the excitation vector

$$\mathbf{g}(t) = \sum_{i=1}^{p} \mathbf{a}_i \cos(\Omega_i t + \psi_i) = \sum_{i=1}^{p} \left(\mathbf{h}_i \sin\Omega_i t + \bar{\mathbf{h}}_i \cos\Omega_i t\right) \tag{2}$$

with the fx1-vector of amplitudes $\mathbf{a}_i$ and the corresponding frequences Ω_i and phase shifts ψ_i, or the coefficients

$$\begin{aligned} h_{ij} &= -a_{ij}\sin\psi_i \quad , \\ \bar{h}_{ij} &= a_{ij}\cos\psi_i \quad , \end{aligned} \tag{3}$$

respectively.

In addition there exist stochastic excitations due to the rough road surface. With the coloured, ergodic, Gaußian stochastic mx1-vector process $\mathbf{u}$ these excitation forces were combined by the function

$$\mathbf{s}(t) = \mathbf{S}\mathbf{u} + \bar{\mathbf{S}}\dot{\mathbf{u}} \tag{4}$$

with the fxm-input matrices $\mathbf{S}$ and $\bar{\mathbf{S}}$ representing the elasticity and viscosity of the tires.

The goal is to determine the parameters of harmonic excitation by unbalances which are included in $\mathbf{h}_i$ and $\bar{\mathbf{h}}_i$, respectively, assuming that frequences Ω_i are known from measurements. An important aspect is, that for the identification only the accelerations $\ddot{\mathbf{z}}(t)$ are measured. Therefore, the model equations have to be transformed to an observer normal form with additional unknown functions $\mathbf{b}_2(t)$ and $\mathbf{b}_3(t)$. From (1), one obtains

$$\begin{aligned} 0 &= -\mathbf{M}\ddot{\mathbf{z}}(t) + \mathbf{g}(t) + \mathbf{s}(t) + \mathbf{b}_2(t) \quad , \\ \dot{\mathbf{b}}_2(t) &= -\mathbf{P}\ddot{\mathbf{z}}(t) + \mathbf{b}_3(t) \quad , \\ \dot{\mathbf{b}}_3(t) &= -\mathbf{Q}\ddot{\mathbf{z}}(t) \quad . \end{aligned} \tag{5}$$

In contrary to the present wheel balancing technology the acceleration measurements on the road have the advantage to include the actual vibrations of the vehicle into the balancing process without changing the dynamic system by a measuring support. The acceleration signals may show relatively high amplitudes also for small unbalances, because of quadratic increase of acceleration amplitudes for increasing speed. In addition, acceleration sensors deliver absolute signals with respect to the inertial frame.

2.2. Covariance Method for Identification

Starting from a measured signal $\tilde{x}(t)$, the first goal is to extract the unbalance signal component. Together with the wheel frequency, signals belonging to unbalanced rotors with the same rotational speed may be separated by cross correlation between the measured signal and an appropiate harmonic model function. Considering the quadratic dependency of unbalance amplitudes on rotor frequency and measuring at some different vehicle speeds the component of unbalancy within the measured signal can be determined, Eismann [10]. Applying this method for calculating the parameters of unbalancy, i. e. its value and angular position, one has to consider the dynamic transfer behaviour of the vibrating vehicle additionally. However, this transfer function is usually not known.

Applying the covariance method for identification of the vehicle system, determination of unknown transfer parameters is combined with determination of unbalance parameters. The covariance method is based on excitation of the system by white noise. Considering the white noise with intensity q^2 as time derivative dw/dt of a Wiener-process w in the sense of generalized functions with variance parameter q^2, mathematically, the real Gaußian, stationary, ergodic noise excitation with zero mean may be found by a linear time-invariant filter written as

$$dv = Cvdt + Wdw \tag{6}$$

with the 2mx1-state vector of the shape filter

$$v = \left[\ \mathbf{u}^T \ \dot{\mathbf{u}}^T \ \right]^T \quad . \tag{7}$$

The dynamical behaviour of the shape filter is given by the matrices $\mathbf{C}$ and $\mathbf{W}$.

To represent the vehicle model by a state equation with excitation exclusively by the noise process dw, the mechanical model of the system has to be extended by modelling the harmonic excitation, too. With the time histories of normalized unbalancy excitation,

$$s_i(t) = \sin \Omega_i t \quad , \qquad c_i = \cos \Omega_i t \tag{8}$$

one gets

$$\dot{\mathbf{d}} = \mathbf{E}^{\Omega}\mathbf{d} \tag{9}$$

assuming p harmonic excitations characterized by the elements of the 2px2p-matrix

$$E^{\Omega}_{jk} = \begin{cases} \Omega_i & \text{if } k = (2i-1) \ , \ j = k+1 \ , \ i = 1(1)p \\ -\Omega_i & \text{if } j = (2i-1) \ , \ k = j-1 \ , \ i = 1(1)p \\ 0 & \text{else} \end{cases} \tag{10}$$

and the 2px1-state vector

$$\mathbf{d} = \left[\; s_1\; c_1\; \dots\; s_i\; c_i\; \dots\; s_p\; c_p \;\right]^T \quad . \tag{11}$$

The covariance method for identification corresponding to Kallenbach [2], [3], introduces a linear filter

$$\dot{\mathbf{y}} = \mathbf{F}\mathbf{y} + \mathbf{G}\bar{\mathbf{x}} \tag{12}$$

with the lx1-state vector $\mathbf{y}$ and the lxl-system matrix $\mathbf{F}$ of the linear filter. The filter is excited through lxnm-input matrix $\mathbf{G}$ by the nmx1-vector $\bar{\mathbf{x}}$ of measured signals. Thus, the vector $\bar{\mathbf{x}}$ is composed of the measurements, the accelerations, the harmonic functions $s_i(t)$ and $c_i(t)$ based on frequency measurements, and the measured road profile, if available.

Composing a fully extended state vector $\mathbf{x}$ to describe the complete system consisting of the mechanical vehicle model, the model of excitation by unbalances, the model of coloured noise excitation and the linear filter, it yields

$$\mathbf{x} = \left[\; \bar{\mathbf{z}}^T\; \mathbf{b}_2^T\; \mathbf{b}_3^T\; \mathbf{d}^T\; \mathbf{y}^T \mathbf{v}^T \;\right]^T \quad . \tag{13}$$

This full system is represented by the stochastic differential equation

$$\mathbf{R}d\mathbf{x} = \mathbf{A}\mathbf{x}dt + \mathbf{B}dw \tag{14}$$

with the Wiener-process w with $E\{w\} \equiv 0$ and $E\{w^2\} \equiv q^2 t$ or $(dw)^2 = q^2 dt$, respectively, with probability 1. The quadratic matrices $\mathbf{R}$ and $\mathbf{A}$ are of the dimension $(3f+2p+l+2m)$, just as the input matrix $\mathbf{B}$. With $\mathbf{A}^* = \mathbf{R}^{-1}\mathbf{A}$ and $\mathbf{B}^* = \mathbf{R}^{-1}\mathbf{B}$ the solution process reads

$$\mathbf{x} = e^{\mathbf{A}^* t}\, \mathbf{x}_0 + \int_0^t e^{\mathbf{A}^*(t-\tau)}\, \mathbf{B}^*\, dw_\tau \tag{15}$$

and the second moments of solution process yield

$$\mathbf{M}_{xx}(t) = e^{\mathbf{A}^* t}\, \mathbf{M}_{xx}(0)\, e^{\mathbf{A}^{*T} t} + \int_0^t e^{\mathbf{A}^*(t-\tau)}\, \mathbf{B}^*\, q^2\, \mathbf{B}^{*T}\, e^{\mathbf{A}^{*T}(t-\tau)}\, d\tau \quad . \tag{16}$$

Differentiation leads to the covariance equation, which is valid for the matrix of second moments $\mathbf{M}_{xx}(t)$ as well as for the corresponding central covariance matrix

$$\tilde{\mathbf{C}}_{xx}(t) = E\left\{(\mathbf{x} - \mathbf{m}_x(t))\,(\mathbf{x} - \mathbf{m}_x(t))^T\right\} = \tilde{\mathbf{C}}_{xx}^T(t) \quad . \tag{17}$$

Then, the covariance equations read

$$\dot{\tilde{\mathbf{C}}}_{xx} = \mathbf{A}^*\, \tilde{\mathbf{C}}_{xx} + \tilde{\mathbf{C}}_{xx}\, \mathbf{A}^{*T} + \mathbf{B}^*\, q^2\, \mathbf{B}^{*T} \quad . \tag{18}$$

With an asymptotically stable matrix $\mathbf{A}^*$, the stationary solution is unique and $\mathbf{C}_{xx} = \lim_{t \to \infty} \tilde{\mathbf{C}}_{xx}(t)$ yields the algebraic Ljapunov matrix equation

$$A^{*}C_{xx} + C_{xx} A^{*T} + B^{*} q^2 B^{*T} = O \quad . \tag{19}$$

The essential relations for identification may be extracted from (18) eliminating the matrices C_{b_2y} and C_{b_3y} analytically. In addition, with the help of a suitable filter matrix $\mathbf{F}$, the quantities which appear in combination with unknown covariances between the measured signals $\ddot{\mathbf{z}}, \mathbf{d}$ and the unknown functions $\mathbf{b}_2$, $\mathbf{b}_3$ can be eliminated numerically. Therefore, the relations obtained from the Ljapunov matrix equation (19) have to be left-multiplied by the numerically generated matrix $\overline{\mathbf{H}}$. Here, the matrix $\overline{\mathbf{H}}$ may be found from the condition

$$\overline{\mathbf{H}}\mathbf{F}^{-1}\Big[\ \mathbf{G}\ \mathbf{F}^{-1}\mathbf{G}\ \Big] \overset{!}{=} \mathbf{O} \tag{20}$$

with the known matrices $\mathbf{F}$ and $\mathbf{G}$. The dimension of $\overline{\mathbf{H}}$ is $l_1 \times l$, where $l_1 = l - 2nm$ mean the number of measured accelerations. Then, it follow the algebraic identification relations

$$- \overline{\mathbf{H}}\mathbf{C}_{y\ddot{z}}\mathbf{M}^T + \overline{\mathbf{H}}\mathbf{C}_{yd}\mathbf{T}^T + \overline{\mathbf{H}}\mathbf{C}_{yu}\mathbf{S}^T + \overline{\mathbf{H}}\mathbf{C}_{y\dot{u}}\overline{\mathbf{S}}^T + \overline{\mathbf{H}}\mathbf{F}^{-1}\mathbf{C}_{y\ddot{z}}\mathbf{P}^T$$
$$+ \overline{\mathbf{H}}\mathbf{F}^{-2}\mathbf{C}_{y\ddot{z}}\mathbf{Q}^T = \mathbf{O} \quad , \tag{21}$$

where the fx2p–matrix $\mathbf{T}$ is given by

$$\mathbf{T} = \Big[\ \mathbf{h}_1\ \overline{\mathbf{h}}_1\ \dots\ \mathbf{h}_i\ \overline{\mathbf{h}}_i\ \dots\ \mathbf{h}_p\ \overline{\mathbf{h}}_p\ \Big] \tag{22}$$

The special structure of mechanical multibody systems can now be utilized. Symbolically generated equations of motion show the elements of the matrices $\mathbf{M}$, $\mathbf{P}$, $\mathbf{Q}$, $\mathbf{S}$, $\overline{\mathbf{S}}$ and $\mathbf{T}$ explicitely as functions of few scalar mechanical parameters like masses, spring coefficients or damper coefficients. Summarizing the unknown mechanical parameters in a $\overline{q} \times 1$-vector $\overline{\mathbf{p}}$ the matrices may be rewritten as

$$\begin{aligned} \mathbf{M} &= \mathbf{M}_0 + \mathbf{M}_L(\overline{\mathbf{p}}) \quad , & \mathbf{P} &= \mathbf{P}_0 + \mathbf{P}_L(\overline{\mathbf{p}}) \quad , \\ \mathbf{Q} &= \mathbf{Q}_0 + \mathbf{Q}_L(\overline{\mathbf{p}}) \quad , & \mathbf{T} &= \mathbf{T}_0 + \mathbf{T}_L(\overline{\mathbf{p}}) \quad , \\ \mathbf{S} &= \mathbf{S}_0 + \mathbf{S}_L(\overline{\mathbf{p}}) \quad , & \overline{\mathbf{S}} &= \overline{\mathbf{S}}_0 + \overline{\mathbf{S}}_L(\overline{\mathbf{p}}) \end{aligned} \tag{23}$$

assuming the matrices $\mathbf{M}_L$, $\mathbf{P}_L$, $\mathbf{Q}_L$, $\mathbf{S}_L$, $\overline{\mathbf{S}}_L$ and $\mathbf{T}_L$ as linear with respect to the elements of parameter vector $\overline{\mathbf{p}}$. Together with this linear parametrization relations (21) lead for K different correlation times τ_k, $k = 1(1)K$, to $K \cdot l_1 \cdot f$ scalar equations for q unknown parameters resulting in an overdetermined linear system of equations,

$$\overline{\mathbf{W}}\overline{\mathbf{p}} = \overline{\mathbf{r}} \quad . \tag{24}$$

The system (24) has to satisfy the following necessary conditions for nontrivial solutions: $K \cdot l_1 \cdot f \geq \overline{q}$ and $\mathbf{M}_0$, $\mathbf{P}_0$, $\mathbf{Q}_0$, $\mathbf{S}_0$, $\overline{\mathbf{S}}_0$ and $\mathbf{T}_0$ must not vanish all at once, i. e. $\overline{\mathbf{r}} \neq \mathbf{O}$.

If the road profile isn't measured, however, the covariance matrices $\mathbf{C}_{yu}$ and $\mathbf{C}_{y\dot{u}}$ are unknown. Without restriction of generality it is further assumed that

$\overline{S} = O$ or $C_{y\hat{u}} = O$, respectively, therefore the tire damper is neglected. Thus $\overline{m}$ unknown excitations u_j leads to $l \cdot \overline{m}$ additional parameters. In this case one has to consider measurements at g different speeds to get sufficient equations. Taking into account the quadratic increase of acceleration amplitudes due to excitation by unbalances, there can be obtained factors λ_{ik}, $k = 2(1)g$, yielding

$$\left(C_{y_i u_j}\right)_1 = \lambda_{i2}\left(C_{y_i u_j}\right)_2 = \ldots = \lambda_{ig}\left(C_{y_i u_j}\right)_g \quad , \qquad i = 1(1)l \quad , \quad j = 1(1)\overline{m} \quad . \tag{25}$$

The factors λ_{ik} depend not only on the unbalances but also on the filter matrix $\mathbf{F}$ and on the frequency response of the vehicle itself. In addition the factors λ_{ik} depend on the spectral density function of the road profile. However, the filter matrix $\mathbf{F}$ is known and the influence of the dynamic behaviour of the vehicle system can be estimated, e. g. considering the measured covariances $C_{y\ddot{z}}$. The dependency on the spectral density function has to be approximated. Thus the number of unknown parameters measured at g different speeds will not increase. In addition, the g sets of equations received are linear independent. Finally, it remains an overdetermined system of equations, as follows,

$$\mathbf{W}\mathbf{p} = \mathbf{r} \quad , \tag{26}$$

containing $g \cdot K \cdot l_i \cdot f$ scalar equations for $\overline{q} + l \cdot \overline{m}$ unknown parameters. The parameter vector $\mathbf{p}$ may be estimated in the sense of least squares by premultiplying (26) with $\mathbf{W}^T$:

$$\mathbf{p} = \left(\mathbf{W}^T\mathbf{W}\right)^{-1}\mathbf{W}^T\mathbf{r} \quad . \tag{27}$$

Fig. 1 shows schematically the information flow for the identification of unbalances using the covariance method.

3. SIMULATION RESULTS

The presented method will be tested by a spatial model of a vehicle. This vehicle model was already used by Rill [11] and consists of five rigid bodies with alltogether seven degrees of freedom. There is one single excentric mass at each front wheel. Fig. 2 shows the vehicle model schematically.

A detailed investigation on the identification of unbalances of the described vehicle with measured excitation by the road was presented by Jung [12]. Jung investigated the influence of vehicle speed on the identification accuracy and the dependency on the eccentricities of the unbalances to be identified. In addition, he considered the mutual interdependences between unbalances at the left and at the right front wheel, the influence of frequency differences between Ω_1 and Ω_2 and the influence of the stabilizer elasticity on the accuracy of identification. Both unbalances could be identified very well, especially, if the wheel frequency was close to the resonance frequency of the wheels. In contrary, very small unbalances lead to weak results, since the unbalance signals were vanishing within the road noise.

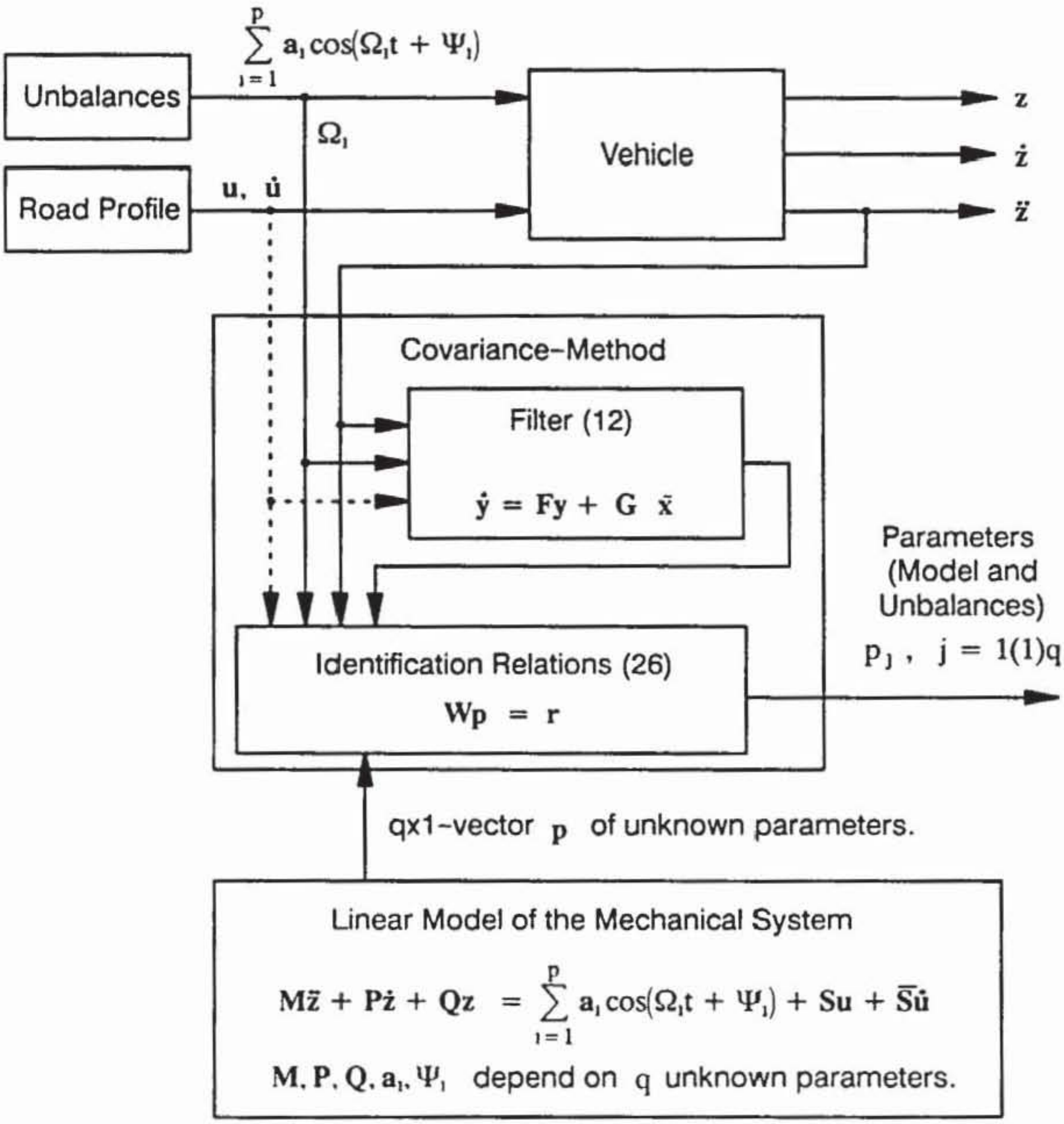

Fig. 1: Covariance Method for Balancing

Further results of the identification of unbalancy at one wheel without measuring the stochastic excitation by the road are shown in Fig. 3. For this simulation time histories at four different driving speeds between 110 km/h and 130 km/h were taken into account. Fig. 3 presents the relative error between the identified and the given parameter values of tire stiffness and mass of unbalancy, and the absolute angular deviation between identified and given location of unbalancy, respectively.

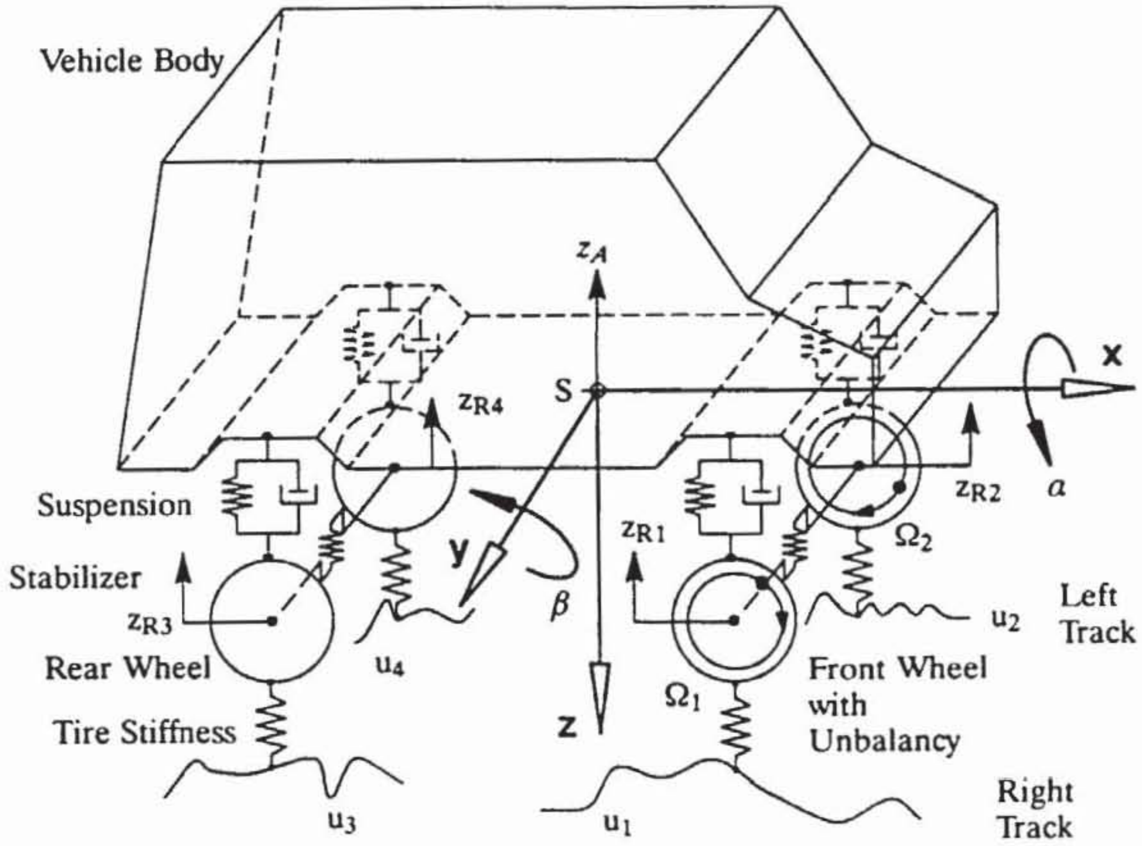

Fig. 2: Spatial Vehicle Model

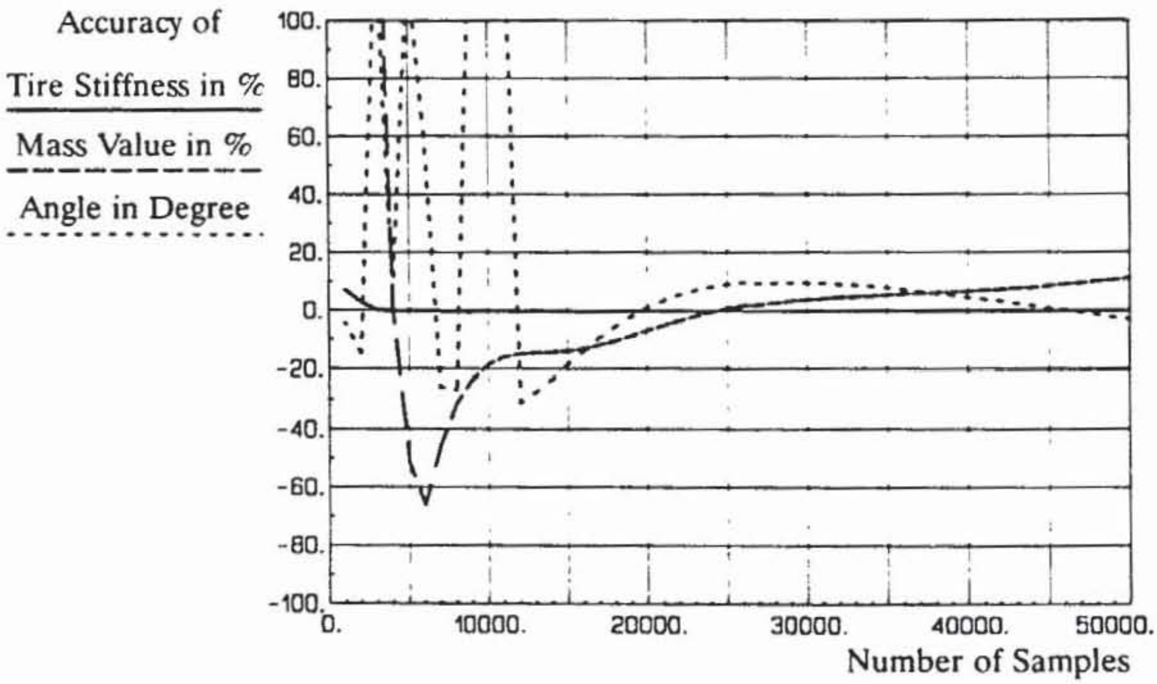

Fig. 3: Accuracy of Identification

The errors are decreasing with the number of samples. Considering more than 20000 samples results in errors less than 10% for the mass value resp. 10 degrees for the angular location. The identification of the tire stiffness needs only 5000 samples. Renunciation of measuring the stochastic excitation by the road leads to a strong loss of information, of course. Therefore, an acceptable result needs more samples and more different speeds. In addition, the ratio of number of equations to number of unknown parameters grows with an increasing filter order of linear filter (12).

Here, the linear filter was chosen as a Butterworth type of order five. Thus, each measured signal leads to five filter signals generated by the state equation of the filter.

As an example the dependency of the scalar values of cross covariances $C_{y_5\ddot{z}_{R1}}$ and $C_{y_5u_1}$ on the normalized speed V is shown in Fig. 4. Here y_5 means the filtered signal of wheel acceleration $\ddot{z}_{R1}$, and u_1 one realization of the road excitation at the right frontwheel. Obviously, the value of $C_{y_5\ddot{z}_{R1}}$ increases nearly as V^4 and the value of $C_{y_5u_1}$ increases nearly as V^2. The covariance $C_{y_5\ddot{z}_{R1}}$ increases slightly more than V^4, since the influence of the frequency response of the vehicle system dominates. In contrary, the increasing covariance value of $C_{y_5u_1}$ is dominated by the decreasing spectral density function of the road surface.

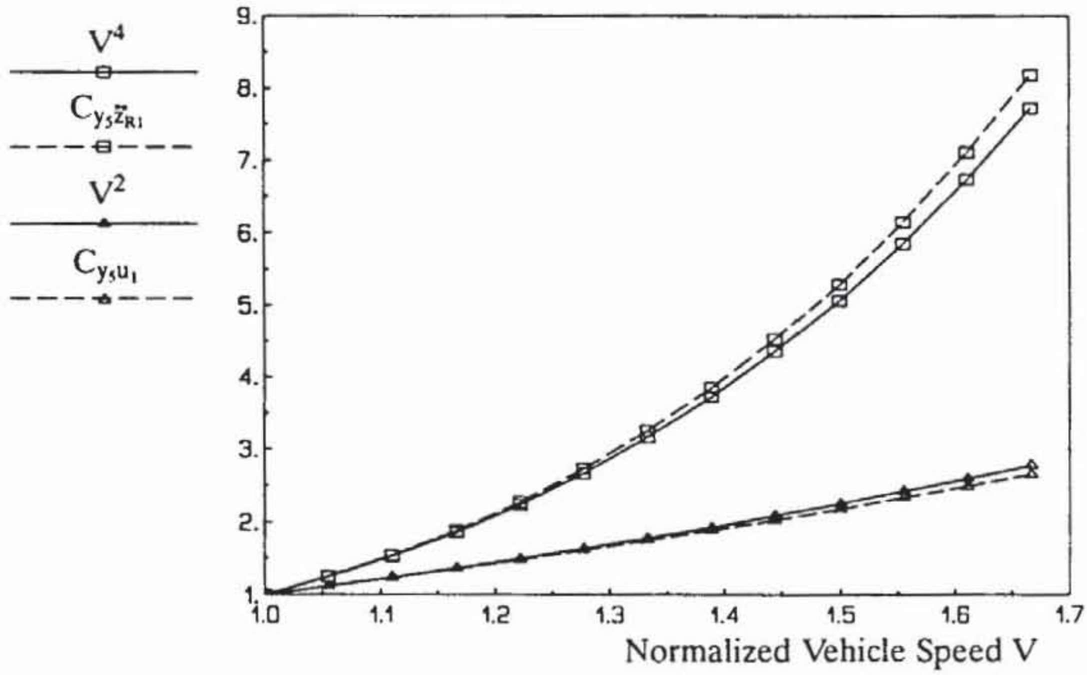

Fig. 4: Relation between Cross-Covariance and Vehicle Speed

4. DESIGN OF TEST VEHICLE

For the validation of the theoretical investigations by an engineering application, a test vehicle will be equipped with a mobile data acquisition system. For the practical tests a standard limousine is to be provided.

The mobile data acquisition system meets the following propositions.

- 12 channels acceleration measurement with preamplifier, anti-aliasing filter and simultaneous A/D-convertion of each channel,
- 2 channels measurement of wheel frequency and angular location of wheel,
- correction of phase shifts between the analogue acceleration channels and the digital wheel impuls transducer signals,
- operating of the measurement equipment via software with the help of a graphical user interface,
- robust mass memory for running while driving on the road,
- long time measurements without loss of information,
- online data processing (FFT, spectral density function, coherence function, transfer function) and online data visualization,
- offline data processing at the face (data reduction and data selection as well as transfer of data to the stationary computer network at the Institute),
- power supply on the basis of 12 V DC and on the basis of 220 V AC as well.

The requirement of long time measurements without any loss of samples and the parallel online data processing can only be met using a multi-processor system. The realization on the basis of transputer technology combines high CPU-power with the possibility of flexible expansion of the system to meet future requirements, like the simulation of multibody systems parallel to measurement data acquisition and processing. The transputer system is controled by a standard mobile 386' laptop as host computer. The present configuration consists of one transputer node T800 with 16 MB DRAM local on chip memory. During the measurements this memory serves as temporary buffer memory. Thus, there is no need to run a hard disk while driving the vehicle. When the measurements are finished the stored data may be transfered to the removeable hard disk of the host computer and may be transfered via the docking station to the stationary computer network to undertake powerful data processing and long time storage of data, too.

With respect to the measurement of wheel frequency there are two possibilities. On the one hand, the standard ABS-system of the test vehicle provides 96 increment pulses per one revolution of the wheel. The advantage of using these signals is, that there is not any change of vibration behaviour of the vehicle and of the wheels, in particular. The disadvantages are the relative rough angular resolution of 3.75 degrees and the need of installing an additional signal source as zero mark to allow the determination of the angle required for the transformation to the axle-fixed coordinate system. On the other hand, a wheel impuls transducer may be fixed at the outer side of the wheel rim and the car-body. This wheel impuls transducer is provided with 1000 pulses per revolution and one puls per revolution as zero mark, additionally. Even more pulses are available if necessary. The disadvantage is given by the load of the wheel puls transducer which changes the dynamic behaviour of the wheel. Further fixing the system at the car-body leads to a disturbing angle deviation by steering the wheel.

There is another problem comparing analogue acceleration signals and digital rotation puls signals. To get suitable samples of analogue signals one needs an anti-aliasing-filter for each channel to hold the Shannon sampling theorem. Thus, in contrary to the increment signals, the signals of acceleration sensors get the phase shift of the filters. To compare the measurement of wheel frequency with the unbalancy signal consisting of only one single frequency one has to compensate that phase shift. However, the online analysis of the signals in the time domain or in the frequency domain, respectively, isn't possible. Therefore, in addition to the puls signals the time discrete angle values and the corresponding sin- and cos-signals were generated and after their D/A-convertion were read as additional analogue input signals. Now, from the filtered sin- and cos-signals one can determine the wheel angle, which has the same phase shift as the acceleration signals because of the identical anti-aliasing-filters. Fig. 5 shows schematically this approach. Finally, Fig. 6 shows the configuration of the complete data acquisition system.

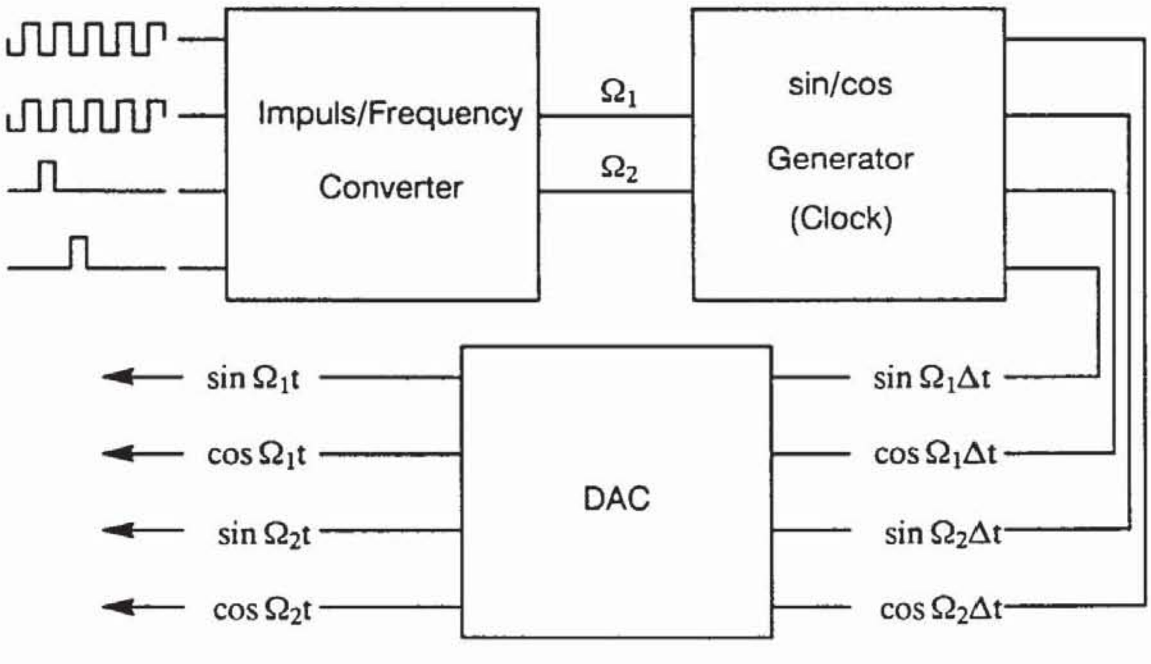

Fig. 5: Signal Conditioning for the Wheel Impuls Transducer

5. CONCLUSION

A method for the identification of unbalances at vehicles while driving was presented. It performs the reduction of unbalances of the wheels as well as the control of other sources of excitation. Therefore, one obtained an overall compensation of harmonically excited vehicle vibrations in a certain speed domain system.

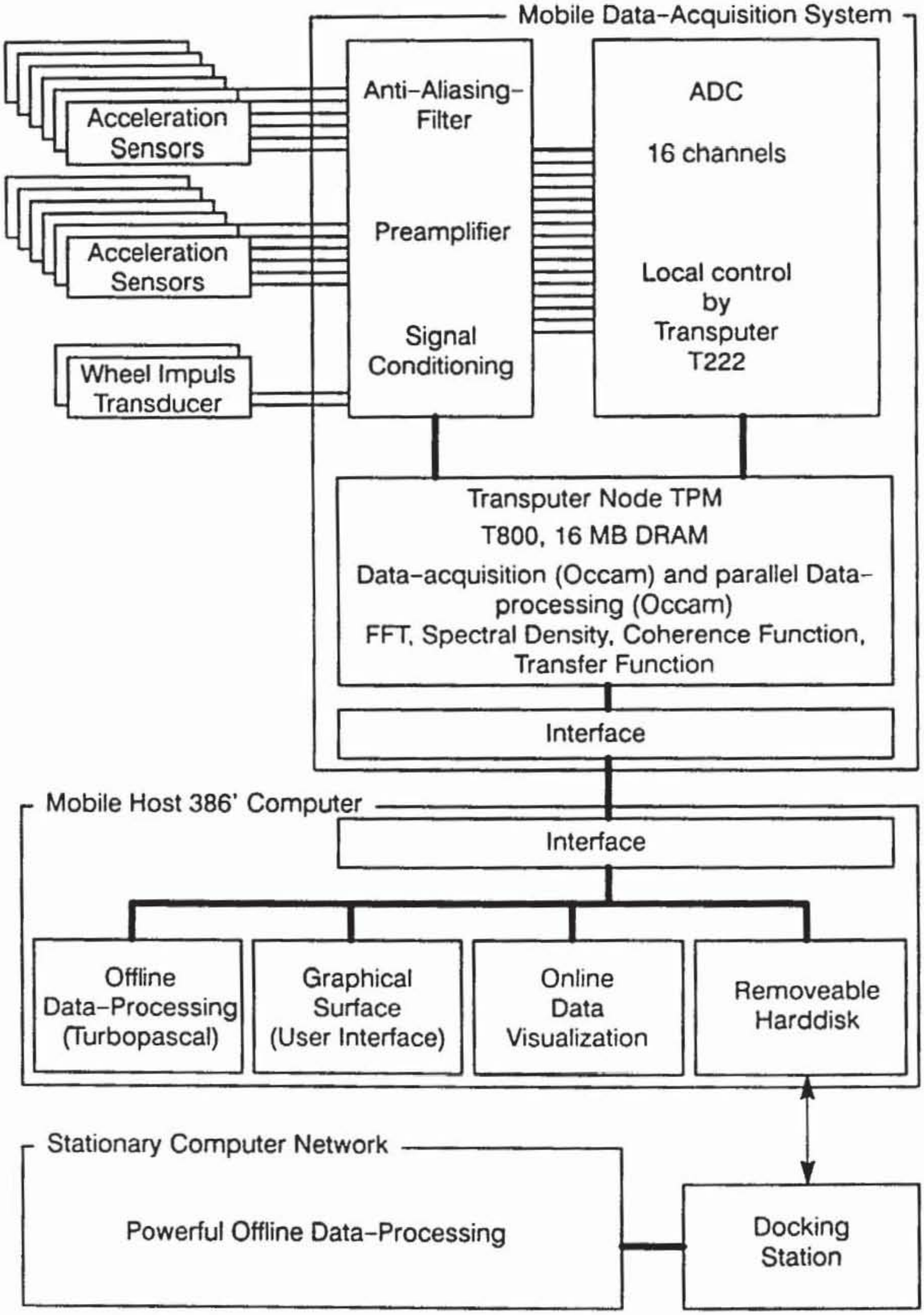

Fig. 6: Configuration of the Data-Acquisition System

The vehicle system was modeled as multibody system. The equations of motion were generated symbolically and transformed to an observer normal form for the identification on the basis of acceleration measurements, exclusively. The excitation by the rough road surface was modeled as a coloured, ergodic Gaußian stochastic process and the covariance analysis was applied to get for the steady-state case of vehicle motion algebraic identification relations using the covariance analysis.

The identification of unbalances was performed without measuring the road profile, leading to additional unknown parameters. In this case, to get sufficient information for the identification, it was simulated at some different vehicle speeds and the quadratic increase of the amplitudes due to vibrations excited by unbalances was taken into account.

Finally the configuration of the mobile data acquisition system was presented which the test vehicle shall be equipped with. The requirement of long time measurements on sixteen channels lead to an implementation using parallel processing by transputer technology.

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