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Estimation of road profile for vehicle dynamics motion: experimental validation

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Abstract— **Knowledge of vehicle dynamic data is essential for the enhancement of active safety systems such as suspensions and trajectory control systems. Vehicle controllability analysis on real roads can be obtained only if valid road profile and tire road friction model are known. With regard to the road profile, this study focuses on a real-time estimation method based on Kalman filter. Besides, this paper presents a method for calculating loads on the wheels using road profile. The proposed method is based on the dynamic response of a vehicle instrumented with available sensors. The estimation process is applied and compared to real experimental data obtained with two inertial methods in real conditions. Experimental results show the accuracy and the potential of the proposed estimation process.**

I. INTRODUCTION

A close examination of accident data reveals that losing vehicle control is the main reason for most of car accidents. Improving vehicle stabilization and control systems is possible if vehicle dynamic variables are known. Unfortunately, because of technical and economic reasons, some of these parameters are not measurable in a standard vehicle, and thus, they must be estimated. For example, in [1], [2] and [3] observers are proposed for sideslip angle, lateral and vertical tire forces estimation without considering the road profile effects. Road profile is seen as an essential input that affects vehicle dynamics data. Hence, an accurate knowledge of this data is essential for a better understanding of vehicle dynamics and control systems design (i.e active and semi-active suspensions design [4]).

For road serviceability, survey and road maintenance, several profilometers are developed, namely the Longitudinal Profile Analyser (LPA) and the General Motor profilometer (GMP). The LPA is an instrument developed by the LCPC (Laboratoire Central des Ponts et Chaussées) french laboratory [5], [6], [7]. It has been the subject of many studies and research. The system includes one or two single wheel trailers towed at constant speed by a car and a data acquisition. Vertical movements of the wheel result in angular travel of the oscillated beam, measured with respect to the horizontal arm of the inertial pendulum, independently of movements of the towing vehicle (see Fig.1). Rough measurements have to be processed to obtain a reliable estimation of the road profile (phase distortion correction). Although this device has proved to give very precise profile elevation measurements, it can not be integrated in ordinary cars. On the other hand, GMP profiler uses accelerometers placed on the body of the measuring vehicle to establish an inertial reference. The recorded profile is obtained by calculating the relative displacement between the accelerometers and the pavement surface [5], [8], [9]. The problem is that the method depends heavily on sensors location and noises.

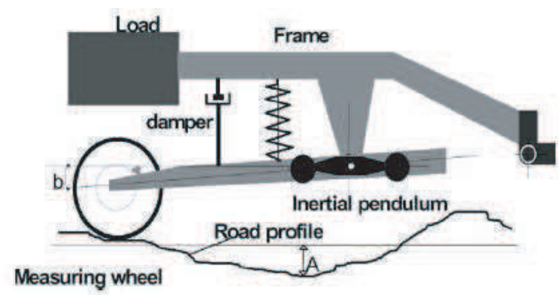

Fig. 1. LPA.

Recently, in [5], [6], a robotic approach based on sliding mode observer was developed in order to estimate the road profiles. The method considered a full car model of 16 Degree Of Freedom (DOF). This complex model could be complicated for real time implementation. The objective of this research in that regard is to develop an embedded observer based on Kalman filter. The proposed method uses measurements from available sensors: accelerometers and suspension deflection sensors. For simplicity reasons, a quarter-car vehicle model is considered. The estimation process consists of two blocks as shown in Fig.2. The first block serves to calculate the vehicle body position from the vertical acceleration signal, while the second block contains a Kalman filter that uses the result of the first block as a measure in order to estimate the road profile elevation and then evaluate loads on the wheels.

The rest of the paper is organized as follows. Section 2 describes the quarter-car model for passive suspension. In section 3 we present the model state space representation and the observability analysis. Section 4 presents the Kalman filter and its consistency. In section 5, experimental tests and results are shown and discussed. Finally, section 6 provides concluding remarks about this study and some perspectives.

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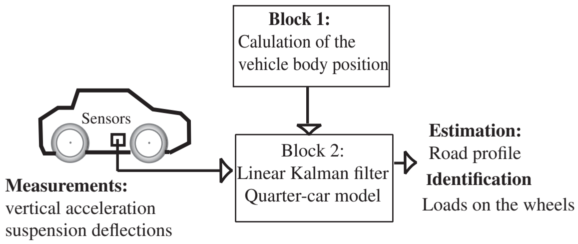

Fig. 2. Estimation process.

II. VEHICLE MODELING

To implement the Kalman filter method, a suitable vehicle model must be assumed. In order to describe the vertical dynamics of a vehicle that runs at a constant speed along an uneven road, 2 DOF quarter-car model (see Fig.3) is considered. The quarter-car model does not take into account pitch and roll motions. Despite its simplicity, it captures the most basic feature of the vertical model of the vehicle [10], [11]. We assume that wheels are rolling without slip and without contact loss, relations (1) and (2) represent the motion of the vehicle body and the wheel respectively,

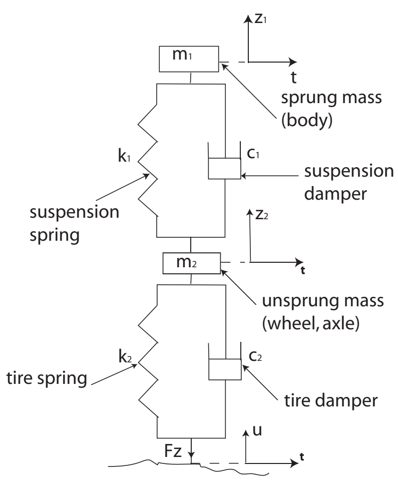

Fig. 3. Quarter car model.

$$\begin{aligned} m_1\ddot{z}_1 &= -k_1 z_1 - C_1\dot{z}_1 + k_1 z_2 + c_1\dot{z}_2 && (1)\\ m_2\ddot{z}_2 &= -(k_1+k_2)z_2 - (c_1+c_2)\dot{z}_2 + k_1 z_1 + \\ &\quad c_1\dot{z}_1 + k_2 u + c_2\dot{u} && (2) \end{aligned}$$

where m_1 and m_2 are respectively the mass of the quarter vehicle body and the wheel, k_1 is the elastic coefficient of the spring incorporated in the suspension system, k_2 is the elastic coefficient of the tire, c_1 is the damping coefficient of the shock absorber, c_2 is the damper coefficient of the tire, z_1 is the position of the vehicle body, z_2 is the position of the wheel, u is the displacement of the road and the dot denotes the time derivative, i.e., $\ddot{z}_1 = \frac{d^2 z_1}{dt^2}$.

The normal force, Fz, commonly named wheels load could be calculated using the following formula :

$$Fz = (m_1+m_2)g - k_2(z_2-u) - c_2(\dot{z}_2-\dot{u}) \quad (3)$$

where g is the gravitational acceleration.

III. MODEL STATE-SPACE REPRESENTATION

Using relations (1) and (2) a linear stochastic state-space representation with no input is developed (the road profile, u, is usually considered as an excitation input to the vehicle, however, as our objective is to estimate u, so it is included in the state-space vector). From first-order Euler approximation discrete form, the above differential equations can be written in a stochastic discrete state-space notation as:

$$\begin{aligned} x_{k+1} &= A_k x_k + b_{m,k} \\ z_k &= H_k x_k + b_{s,k}, \end{aligned} \quad (4)$$

where

- $x_k = (z_{1,k}\ \dot{z_{1,k}}\ z_{2,k}\ \dot{z}_{2,k}\ u_k\ \dot{u_k})^T$ is the state vector ; the initial state vector is null ;
- $z_k = ((z_{1,k}-z_{2,k})\ z_{1,k}\ \ddot{z}_{1,k})^T$ is the observation vector where :
  - $z_{1,k}-z_{2,k}$: suspension deflections measured from sensor ;
  - $z_{1,k}$: vehicle body position calculated by a double numerical integration (trapezoidal method) of the filtered vertical acceleration signal.
  - $\ddot{z_{1,k}}$: filtered vertical acceleration.
- The road profile ,u, is presented in a random walk model ($\ddot{u} = 0$)
- $b_{m,k}$ and $b_{s,k}$ are the process and measurement noise vectors respectively, assumed to be white, zero mean and uncorrelated.

Evolution and observation constant matrices of the system respectively A and C are given as:

$$\mathbf{A} = I + te \begin{pmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ -\frac{k_1}{m_1} & -\frac{C_1}{m_1} & \frac{k_1}{m_1} & \frac{C_1}{m_1} & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ \frac{k_1}{m_2} & \frac{C_1}{m_2} & -\frac{(k_1+k_2)}{m_2} & -\frac{(C_1+C_2)}{m_2} & \frac{k_2}{m_2} & \frac{C_2}{m_2} \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}$$

$$\mathbf{H} = \begin{pmatrix} 1 & 0 & -1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ -\frac{k_1}{m_1} & -\frac{C_1}{m_1} & \frac{k_1}{m_1} & \frac{C_1}{m_1} & 0 & 0 \end{pmatrix}$$

where I is the identity matrix and te is the sampling period.

A. Observability analysis

Observability is a measure of how well internal states of a system can be inferred by knowledge of its input and external outputs. The system described above is a linear observable system. Indeed, it is verified that the observability matrix O has full rank :

$$O = \begin{pmatrix} H & HA & HA^2 & HA^3 & HA^4 & HA^5 \end{pmatrix}^T. \quad (5)$$

IV. KALMAN FILTER CONCISTENCY

The Kalman filter is essentially a set of mathematical equations that implement a predictor-corrector type estimator ([12], [13]). It is optimal in the sense that it minimizes the estimated error covariance when some presumed conditions are met. Assuming that noises are Gaussian, white and centered, Q_k, R_k the noise variance-covariance matrices

for $b_{m,k}$ and $b_{s,k}$ respectively, $\widehat{x}_{k/k-1}$ and $\widehat{x}_{k/k}$ are state prediction and estimation vectors, respectively, at time t_k, the linear Kalman filter for a system with no inputs required the following equations:
Predict next state, before measurements are taken:

$$\begin{array}{rcl} \widehat{x}_{k/k-1} & = & A_k \widehat{x}_{k-1/k-1} \\ P_{k/k-1} & = & A_k P_{k-1/k-1} A_k^t + Q_k \end{array} \quad (6)$$

Update state, after measurements are taken:

$$\begin{array}{rcl} K_k & = & P_{k/k-1} H_k^t (H_k P_{k/k-1} H_k^t + R_k)^{-1} \\ \widehat{x}_{k/k} & = & \widehat{x}_{k/k-1} + K_k (z_k - H_k \widehat{x}_{k/k-1}) \\ P_{k/k} & = & (I - K_k H_k) P_{k/k-1}, \end{array} \quad (7)$$

where K is the Kalman gain used in the update data, P is the covariance matrix for the state estimate containing information about the data accuracy.

Assuming that distributions are Gaussian, a statistical test for real-time consistency can be carried out on the Normalized Innovation Squared (NIS) ([14]):

$$\gamma_k^T S_k^{-1} \gamma_k \leq \chi^2_{r,1-\alpha} \quad (8)$$

where $\gamma_k = z_k - \widehat{z}_k$ is the innovation of the filter, $\widehat{z}_k$ is the observation, S_k is the innovation variance, $\chi^2_{r,1-\alpha}$ is a threshold obtained from the χ^2 distribution with $r = dim(\gamma_k)$ degrees of freedom, and α the desired significance level (usually 0.05).

V. EXPERIMENTAL RESULTS

In this section, the estimation method is compared with the LPA and the GMP profiles using two different equipped vehicles.

A. Comparison with the LPA signal

The experimental vehicle shown in Fig.4 is the LCPC Laboratory's test vehicle. It is a Peugeot 406 equipped with accelerometers, relative suspension deflections sensor and towing LPAs. The vehicle parameters were identified at the LCPC Laboratory and are given in Table 1. Among numerous experimental tests, we consider a test made at the LCPC where the car runs on an irregular surface with a constant speed of $72 km.h^{-1}$. In this experiment, the signal measured by the LPA is considered as reference profile.

Fig. 4. LCPC experimental vehicle towing the LPA.

m_1	$345\ kg$
k_1	$20818\ N/rad$
c_1	$300\ N.m^{-1}.s$
m_2	$40\ kg$
k_2	$100000\ N/rad$
c_2	$500\ N.m^{-1}.s$

TABLE I
LCPC VEHICLE PARAMETERS.

In the following, the estimation results and the LPA signal of the left front wheel are compared. Fig.5 shows the measured vertical acceleration and the relative suspension deflections. To eliminate the noise and calculate the vehicle body displacement, the acceleration signal was filtered by a passband filter [0.5HZ-15Hz].

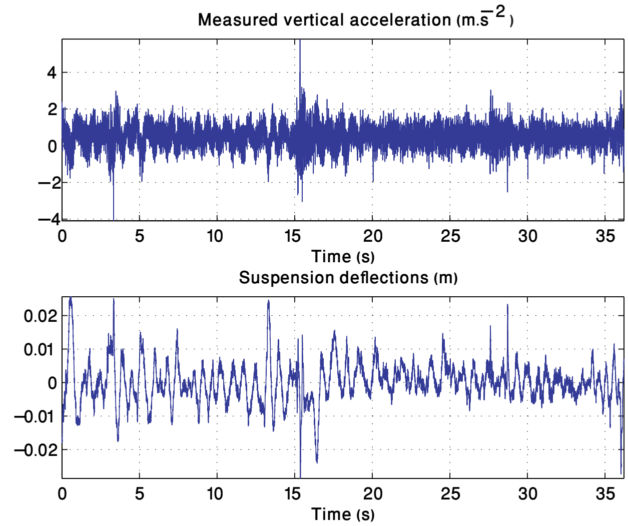

Fig. 5. Vertical acceleration and relative suspension deflections signals.

Although time integrations seem to be straightforward, there are hidden difficulties that can spoil the final results. When integrating, signal low frequencies contents are strongly amplified, high frequencies are reduced and phase is changed [15]. Fig.6 presents the filtered acceleration signal and the calculated vertical displacement of the vehicle body by integration of the filtered acceleration signal. Fig. 7 presents both the measured road profile (from the LPA) and the estimated profile. We can deduce that the estimated values follows the LPA signal. However, some differences of amplitudes persist. They can be due to sensor calibration and to filtering process. Although the filtration and the integration phase induce delay on signal processing, the observer is able to give good results. The consistency evolution along the complete trajectory is presented in Fig.8. We conclude that the observer remains consistent (up to 5% statistical error) during the complete vehicle trajectory.

B. Comparison with the GMP signal

The INRETS-MA vehicle (see Fig. 9) is a Peugeot 307 equipped with a number of sensors, including accelerometers

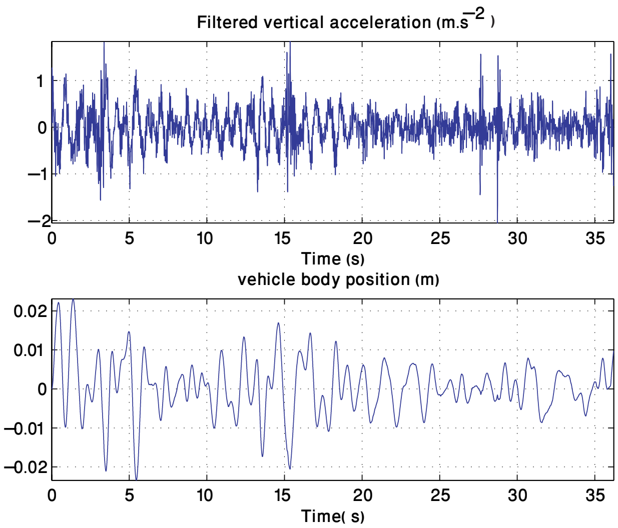

Fig. 6. Filtered acceleration and body displacement signal.

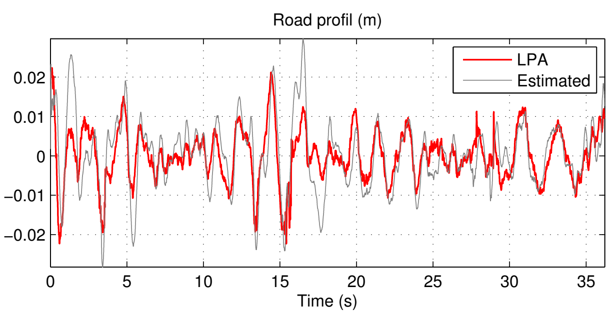

Fig. 7. Comparison between LPA and estimated profile.

that measure vehicle's body longitudinal, lateral and vertical accelerations, relative suspension deflections sensors and dynamometric hubs that measure in real time the forces acting at the tire-road contact point. For more information about the vehicle equipments (software+hardware) and parameters, reader is invited to read [16]. In this test, the vehicle run on an irregular surface at a constant speed of 15 km/h, in addition one plate was situated on the roadway in order to further excite the vehicle dynamics (see Fig.10). To obtain the road profile, the inertial method consist to subtract the absolute motion of the vehicle body and the distance between the vehicle body and the road [5]. The absolute motion is obtained by a double integration of the vertical accelerometer signal, while the distance between the vehicle body and the road is measured by a light sensor. As in the previous subsection, band pass numerical filters were applied in order to eliminate noises. In the following, we compare the GMP signals and the estimated ones for the profile revealed by the four wheels. In Fig. 11 and Fig.12, we show that observers applied for each vehicle corner are able to estimate well the road and the plate. The results confirmed the efficiency of the developed method.

Once road profiles are estimated, it is possible, using equation (3), to calculate the vertical forces on each wheels. In the following, we propose to compare the measured

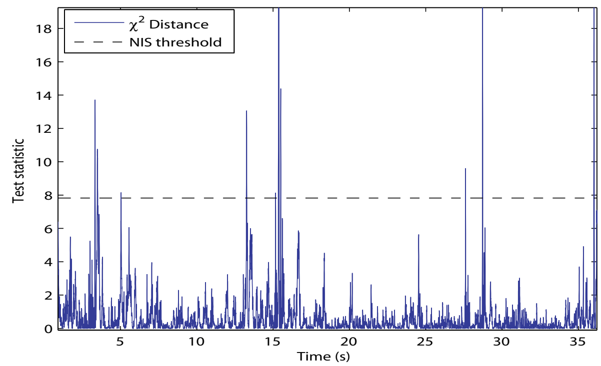

Fig. 8. Observer consistency.

Fig. 9. INRETS-MA experimental vehicle.

vertical forces obtained by the dynamometric hubs and the calculated ones. In Fig. 13 and Fig. 14, the loads applied respectively on the front and rear wheels for the first 8 seconds are represented. The effect of the road irregularities on the normal forces variations is clear. These figures show that the calculated and the measured forces are very close.

VI. CONCLUSIONS AND FUTURE WORKS

The knowledge of the road profile is considered as an essential data when studying vehicle motion and developing active safety systems. This paper has presented a new method to estimate the road profile elevation based on classical Kalman filter. The simplicity of the considered model enables its functioning in real time applications. Compared with experimental real situations, the estimation process was good and correct. Moreover, filter consistency was studied and proved.

It has been shown that by estimate the road profile, we can calculate load on wheels taking into account suspension dynamics.

Our work currently in progress consists of profiles estimation validation in more real situations (case of cornering and variable speed motion).

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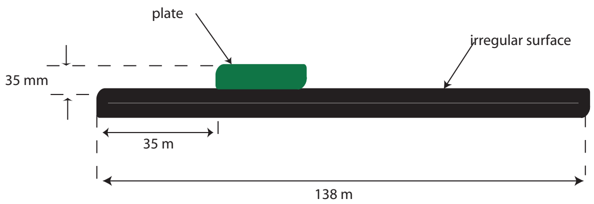

Fig. 10. Experimental track.

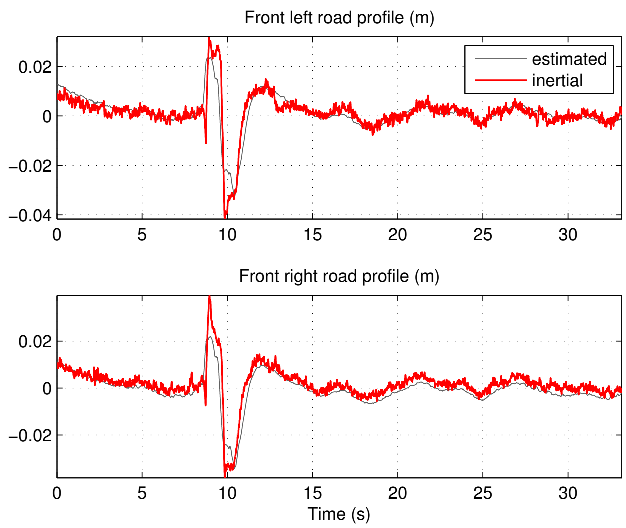

Fig. 11. Road profiles revealed by front wheels.

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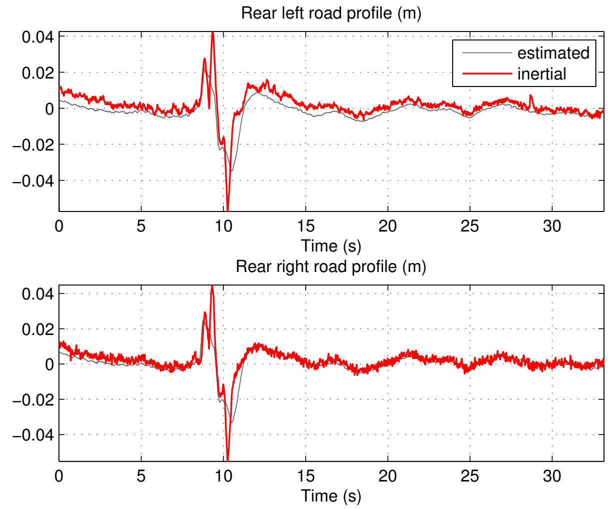

Fig. 12. Road profiles revealed by rear wheels.

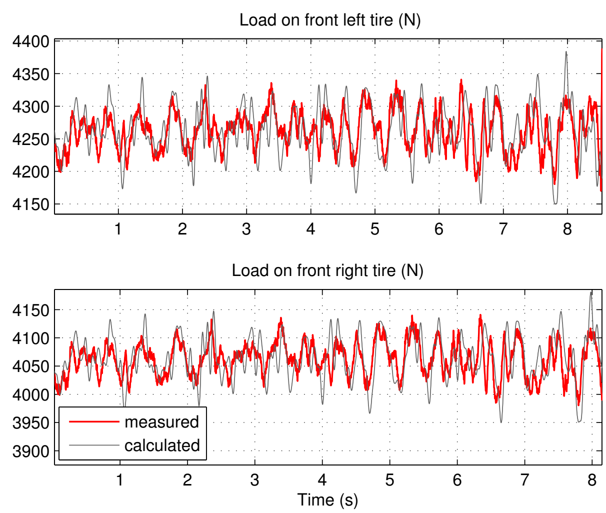

Fig. 13. Load on the front wheels.

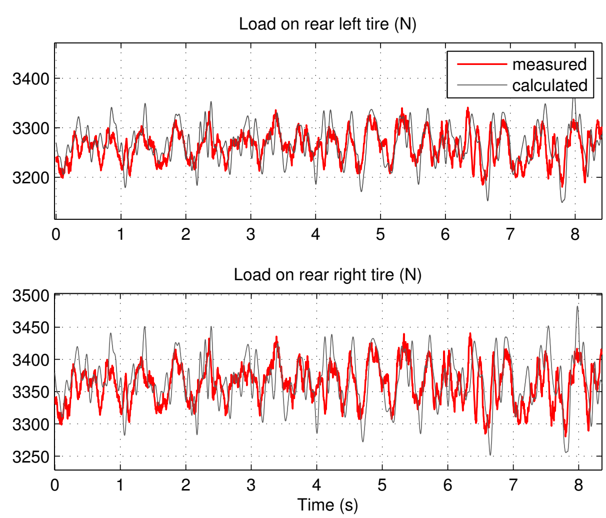

Fig. 14. Load on the rear wheels.

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