A UNIFIED APPROACH TOWARDS FAULT DETECTION OF VEHICLE LATERAL DYNAMICS SENSORS

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Abstract: Vehicle dynamics control systems require a close monitoring of the associated sensors since an erroneous intervention of the controller due to faulty measurements may have fatal consequences. Hardware failures with an immediate impact on sensor signals are detected by build-in sensor tests in connection with a plausibility check of the electrical signals. Slowly growing sensor offsets on the other hand require model based monitoring. Actually, simple stationary models are used to detect these slow changes. Simplicity of the models, however, must be compensated for by an excessive exception handling in order to avoid false alarms due to non-valid models. In this paper, an invariant relation for the signals capturing vehicle lateral dynamics is derived. Based on this relation a novel scheme for vehicle lateral dynamics sensor monitoring is proposed which drastically reduces the necessary exception handling and which keeps up simultaneously with the advantage of simple models.

Keywords: Fault detection; vehicle lateral dynamics; anti-spin regulation; automotive systems

1. INTRODUCTION

In recent years vehicle dynamics control (VDC) systems which support the driver in critical driving situations (as e.g. the ESP system from Bosch (van Zanten *et al.*, 1995; van Zanten *et al.*, 1998)) have been introduced. These systems use signals to derive the drivers intent (steering wheel angle, brake pressure, engine torque) and they compare it with the actual vehicle motion (yaw rate, lateral acceleration). In case of deviations between actual and intended motion corrective actions by means of controlled braking of individual wheels are initiated by the system. Since this intervention is safety critical, the underlying measurements related to lateral dynamics (i.e. steering wheel angle, yaw rate, and lateral acceleration) closely have to be monitored for possible faults.

Sensor monitoring typically includes three different layers (Isermann, 1997). The first layer contains sensor build-in test procedures which basically check sensor hardware for failures (Henry and Clarke, 1993). Signal-individual tests for signal plausibility (physical limits) and signal characteristics (e.g. periodicity or statistical properties) make up the second layer (see also (Basseville and Nikiforov, 1993)). In the third layer, relations between signals are checked by means of process models (Frank, 1990).

The different layers not only classify different fault detection mechanisms but also indicate an ordering with respect to detection time: while the build-

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in tests in the first layer are intended to detect a sudden hardware fault, model-based methods in the third layer aim at the detection of slowly growing sensor offsets. However, also abrupt changes can be detected with these methods.

Since the different layers are capable to detect different kinds of faults typically more than one layer is realized within a monitoring system. For a safety critically critical system like a VDC system all layers are encountered (Robert Bosch GmbH, 1998; Ding *et al.*, 2004).

In this paper the focus is on the third layer, namely on a model based signal plausibility test. Typically, simple kinetic and kinematic models in combination with further simplifying assumptions (stationary driving on circular roads) are used in this layer (Börner, 2004; Ding *et al.*, 2004). The reasons for using rather simple models are real-time limitations on the one hand. On the other hand all vehicle models face the same problem, i.e. unknown, fast time-varying parameters describing the force generation at the tire-road interface (Gustafsson, 1998). Therefore more complex models do not offer a significant advantage.

Sensor signal monitoring is then based on the residual, i.e. the difference between measured signals and corresponding model based estimates (either from forward calculations or as output of an observer scheme). Sufficiently large thresholds for the residuals combined with explicit conditions for model validity are used to account for the model uncertainties. Errors in the dynamical order of the employed models and measurement outliers are considered by requiring a certain number of succeeding threshold violations before a failure is declared. Further improvements are possible by means of adaptive thresholds (Chen and Patton, 1999).

A major problem of the outlined approach is that even stationary driving situations may lead to residuals. This is especially the case for banked curves since the (unknown) lateral inclination angle is neglected in the employed stationary models. However, roads almost always have a small lateral inclination angle in order to let rain water drain off the road surface. More important with respect to the size of artificial residuals are banked curves at mountain passes and at proving grounds. These conditions only make up a small percentage of a typical vehicle life, but a large percentage in vehicle tests from automotive oriented media. Thus false alarms, especially for the mentioned types of roads, absolutely must be avoided. State of the art to overcome this problem is an involved situation detection and exception handling.

In this paper a novel approach towards monitoring of vehicle lateral dynamics sensors is presented that is based on a model of the most general case of stationary driving, i.e. driving in banked curves is included as a special case. It turns out that an invariant relation holds true for lateral acceleration, yaw rate, steering angle, and vehicle velocity – especially this relation is independent from the lateral inclination of the road. With the introduction of a residual for this relation it is then possible to realize a simple fault detection scheme.

In detail the article is structured as follows. Firstly the considered road geometry and the corresponding vehicle motion is presented. Expressions for the (idealized) sensed signals in terms of vehicle velocity and geometric data are derived in the next section. Based on these expressions an invariant relation between the lateral sensors is derived and implications are discussed. The usage of this invariant relation in a fault detection scheme is outlined in the follwing section. A brief summary concludes the paper.

2. STATIONARY DRIVING ON A HELIX

With stationary driving on a helix we mean that the position $\boldsymbol{r}(t)$ of the center of gravity (CoG) of the vehicle at time t is given by

$$\boldsymbol{r}(t) = \Big[R\cos(\omega t),\ R\sin(\omega t),\ h\frac{\omega}{2\pi}(t-t_0)\Big]^{\mathrm{T}} \quad (1)$$

(in Cartesian coordinates x, y, z) for some constant parameters R, h, $\omega > 0$. This means that the motion of the CoG is restricted to the helix given by (1) for $t_0 \le t \le t_e$ where t_0, t_e denotes the starting-time respectively end-time of the considered motion. While R, h describe geometric properties, the helix is ω-invariant. However, the value ω is directly related to the absolute value v of the velocity of the CoG:

$$v = |\dot{\boldsymbol{r}}(t)| = \omega\sqrt{R^2 + \left(\frac{h}{2\pi}\right)^2}. \quad (2)$$

In the following the vehicle pitch and roll motion relative to the road is neglected. Thus the CoG can be assumed to lie at street level (Wong, 2001). The virtual road that supports the CoG motion

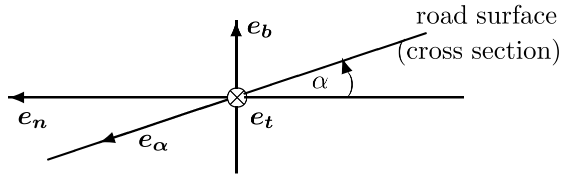

Fig. 1. Definition of bank angle α.

described by (1) is assumed to be a smooth surface that locally is approximated by its tangent planes: if $\boldsymbol{e_t}$, $\boldsymbol{e_n}$, and $\boldsymbol{e_b}$ denote the normalized tangent vector, the normal vector, and binormal

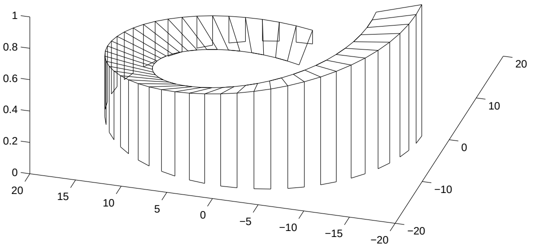

Fig. 2. Schematic representation of a banked curve with slope.

vector, respectively, for a given point of (1), the corresponding tangent plane is spanned by $\boldsymbol{e_t}$ and a vector $\boldsymbol{e_\alpha}$ that lies in the $\boldsymbol{e_n}$, $\boldsymbol{e_b}$-plane with $\boldsymbol{e_\alpha}$ and $\boldsymbol{e_n}$ enclosing a constant angle α independent from the considered point of the curve (see also Fig. 1). A sketch of the constructed road is given in Fig. 2).

"Stationary driving on a helix" is intended to model vehicle movement in banked curves with longitudinal inclination, e.g. for certain mountain passes. However, the situation described above is completely general in the sense that all stationary driving situation are included for a suitable choice of parameters in (1): for $h = 0$ one has a circular movement in the plane, $R \to \infty$ results in straight line driving.

Additionally to road geometry and position of the CoG, the slip angle β, i.e. the angle between longitudinal axis of the vehicle and velocity vector, is necessary to describe the position of the vehicle completely. Due to the stationarity assumption the slip angle is constant for the considered motion.

The implications of this set-up for sensors fixed to the vehicle are considered in the following section. For the corresponding derivations it is convenient to introduce the radius of curvature ϱ of the helix and the inclination angle γ (see also (do Carmo, 1976)):

$$\varrho = R + \frac{1}{R}\left(\frac{h}{2\pi}\right)^2, \quad \cos\gamma = \frac{2\pi R}{\sqrt{(2\pi R)^2 + h^2}}. \tag{3}$$

3. IDEALIZED SENSOR MODELS

In the following it is assumed that the vehicle position is determined by the local tangent plane at the road surface. This is already a simplification since the tangent planes at the wheels are different from the one at the CoG. However, with vehicle dimensions being small compared to the helix radius R, the corresponding effects remain negligible.

3.1 Turn Rate Sensors

It is immediate from (1) that the total angular velocity of the vehicle is given by $\boldsymbol{\omega_{ges}} = \omega \boldsymbol{e_z}$ with $\boldsymbol{e_z}$ being a unit vector which defines the z-coodinate in (1). Decomposition in terms of the natural basis ($\boldsymbol{e_t}$, $\boldsymbol{e_n}$, $\boldsymbol{e_b}$) leads to

$$\boldsymbol{\omega_{ges}} = \omega\cos\gamma\boldsymbol{e_b} + \omega\sin\gamma\boldsymbol{e_t} \tag{4}$$

$$\text{or} \quad \boldsymbol{\omega_{ges}} = \frac{v}{\varrho}\boldsymbol{e_b} + \frac{2\pi v h}{(2\pi R)^2 + h^2}\boldsymbol{e_t}. \tag{5}$$

The yaw rate sensor fixed to the vehicle measures the component of $\boldsymbol{\omega_{ges}}$ perpendicular to the road surface. Due to the introduction of the bank angle α, i.e. as a rotation angle around $\boldsymbol{e_t}$, only the projection of the component in $\boldsymbol{e_t}$-direction of $\boldsymbol{\omega_{ges}}$, i.e.

$$\omega_{z,S} = \omega\cos\gamma\cos\alpha = \omega\frac{v}{\varrho}\cos\alpha\,, \tag{6}$$

is actually measured.

3.2 Acceleration Sensors

Modern micro-mechanical acceleration sensors realize the seismic principle (Stein, 2001). This means that a hypothetical 3-D acceleration sensor mounted in the CoG of a moving vehicle measures

$$\boldsymbol{a_S} = \boldsymbol{a_f} - \boldsymbol{g}, \tag{7}$$

i.e. a combination of the forcing acceleration $\boldsymbol{a_f}$ and the acceleration of gravity $\boldsymbol{g}$. In reality no 3-D accelerations are measured but components of $\boldsymbol{a_S}$ in fixed vehicle directions. Thus measured accelerations depend on lateral inclination, bank angle, and slip angle. In the following this dependency is explicitly derived for the lateral acceleration sensor. The prevalent convention is to consider a CoG-fixed coordinate system (x_F, y_F, z_F) with positive x_F, y_F, z_F in longitudinal front direction, lateral left direction, and vertical up direction, respectively. Therefore the lateral acceleration sensor measures the y_F component of $\boldsymbol{a_S}$ given in vehicle fixed coordinates.

In order to evaluate $\boldsymbol{a_S}$, the right hand side of (7) has to be expressed in vehicle fixed coordinates. However, $\boldsymbol{a_f}$ is most natural expressed in terms of ($\boldsymbol{e_t}$, $\boldsymbol{e_n}$, $\boldsymbol{e_b}$) while the simplest expression for $\boldsymbol{g}$ is given in inertial coordinates. With transformation matrices T_γ, T_α, $T_{-\beta}$ given as

$$T_\gamma = \begin{bmatrix} \cos\gamma & 0 & \sin\gamma \\ 0 & 1 & 0 \\ -\sin\gamma & 0 & \cos\gamma \end{bmatrix}, \quad T_\alpha = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\alpha & -\sin\alpha \\ 0 & \sin\alpha & \cos\alpha \end{bmatrix},$$

$$T_{-\beta} = \begin{bmatrix} \cos\beta & -\sin\beta & 0 \\ \sin\beta & \cos\beta & 0 \\ 0 & 0 & 1 \end{bmatrix}. \tag{8}$$

Eq. (7) can be written in vehicle fixed coordinates as

$$\boldsymbol{a_S} = \begin{bmatrix} a_{x_F,S} \\ a_{y_F,S} \\ a_{z_F,S} \end{bmatrix} = T_{-\beta} \cdot T_\alpha \begin{bmatrix} 0 \\ v^2/\varrho \\ 0 \end{bmatrix} - T_{-\beta} \cdot T_\alpha \cdot T_\gamma \begin{bmatrix} 0 \\ 0 \\ -g \end{bmatrix}. \tag{9}$$

Here the transformation T_γ considers the inclination angle of the helix, T_α account for the bank angle, and $T_{-\beta}$ describes the rotation of the vehicle-fixed coordinate system within the road surface. The expression $\boldsymbol{a_f} = [0, v^2/\varrho, 0]^{\mathrm{T}}$ can be interpreted as forcing acceleration for a point mass motion on the circle of curvature for the helix. Although the circle of curvature is only a local approximation for the helix the equation for $\boldsymbol{a_f}$ is exact (this can be shown by differentiation of (1)).

The measured lateral acceleration signal now can be derived from the second component of (9):

$$a_{y_F,S} = \frac{v^2}{\varrho} \cos\beta \cos\alpha + \\ + g\left(\sin\beta \sin\gamma - \cos\beta \cos\gamma \sin\alpha\right). \tag{10}$$

3.3 Steering Angle Sensor

Assuming an constant transmission ratio i_L for the steering mechanism, the measured steering wheel angle $\delta_{L,S}$ is given as

$$\delta_{L,S} = i_L \delta_R \tag{11}$$

with δ_R being the steering angle at the wheels. For a prescribed vehicle motion, i.e. the movement on a helix with a fixed slip angle, the steering angle becomes a function of road geometry and vehicle velocity. In order to derive an explicit expression for the steering angle, models for the force generation at the tires and vehicle kinematics are necessary. The linear tire model (tire side slip constants c_V, c_H)

$$S_V = c_V \cdot \alpha_V, \quad S_H = c_H \cdot \alpha_H, \tag{12}$$

describes the side forces S_V, S_H at the front and rear tires as linear function of the slip angles α_V, α_H (see Figure 3). This description models the force generation at the tires for a wide range of vehicle operating conditions quite well (Wong, 2001). The tire model is not further detailed for left and right wheels since the employed simplified kinematics depicted in Figure 3 is based on a fusion of the tires at one axis into a substitute tire at the symmetry axis of the vehicle. Therefore the terminology *single track model* or *bicycle model* is frequently used (Mitschke and Wallentowitz, 2004).

However, due to longitudinal and lateral inclination the expressions for the side forces from the standard single track model do not hold anymore for driving on the helix. In this case an impulse balance in the direction $\boldsymbol{e_\alpha}$ (see Figure 1)

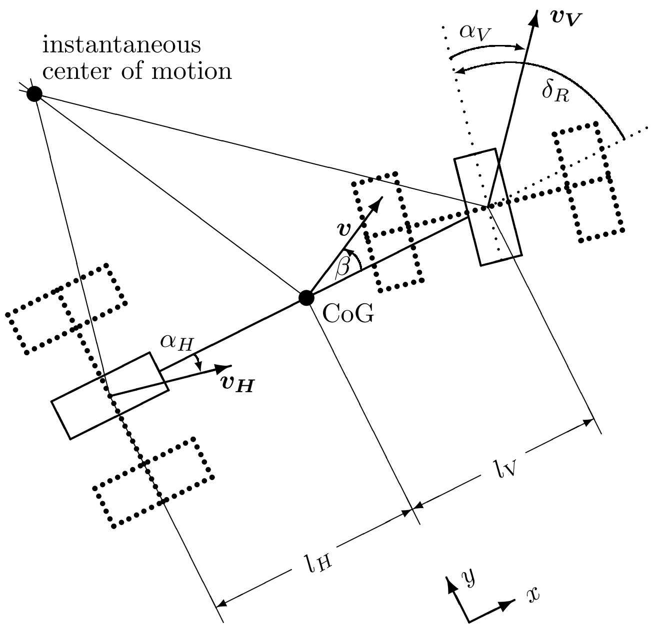

Fig. 3. Scheme of the single-track model.

$$m\frac{v^2}{\varrho}\cos\alpha = S_V \cos\delta_R \cos\beta + \\ + S_H \cos\beta + mg\cos\gamma\sin\alpha \tag{13}$$

together with the angular momentum balance

$$0 = S_V \cdot l_V \cdot \cos\delta_R - S_H \cdot l_H \tag{14}$$

in the local tangent plane to the road surface renders (with $l = l_V + l_H$, $\cos\beta \approx 1$, $\cos\delta_R \approx 1$) the side forces

$$S_H = \frac{l_V \cdot m \cdot g}{l} \cos\alpha \left(\frac{v^2}{\varrho \cdot g} - \tan\alpha\cos\gamma\right), \tag{15}$$

$$S_V = \frac{l_H \cdot m \cdot g}{l} \cos\alpha \left(\frac{v^2}{\varrho \cdot g} - \tan\alpha\cos\gamma\right). \tag{16}$$

The steering angle δ_R follows from the kinematic expression $\boldsymbol{v} = \boldsymbol{v}_0 + \boldsymbol{\omega} \times \boldsymbol{r}$ for the velocity distribution of a rigid body. Applied to the center points of front and rear axis the equations

$$v\cos\beta = v_V \cos(\delta_R - \alpha_V), \tag{17}$$
$$v\cos\beta = v_H \cos\alpha_H, \tag{18}$$
$$v_V \sin(\delta_R - \alpha_V) = v\sin\beta + l_V \cdot \omega_{z,S}, \tag{19}$$
$$-v_H \sin\alpha_H = v\sin\beta - l_H \cdot \omega_{z,S}. \tag{20}$$

follow for longitudinal (17), (18) and lateral (19), (20) direction. These equations imply

$$\tan(\delta_R - \alpha_V) = \tan\beta + \frac{l_V \cdot \omega_{z,S}}{v\cos\beta},$$
$$\tan(\alpha_H) = -\tan\beta + \frac{l_H \cdot \omega_{z,S}}{v\cos\beta},$$

which in turn (together with (6) and the "small angle simplifications" for δ_R, β, α_V, α_H) renders the steering angle δ_R:

$$\delta_R = \alpha_V - \alpha_H + \frac{l}{\varrho}\cos\alpha. \qquad (21)$$

From (11), (21), (12), (15) (16) and with the abbreviation

$$v_c^2 = \frac{c_V \cdot c_H \cdot l^2}{m \cdot (l_H \cdot c_H - l_V \cdot c_V)}$$

we finally have

$$\delta_{L,S} = i_L \left(\frac{l\cos\alpha}{\varrho} \left(1 + \left(\frac{v}{v_c}\right)^2\right) - \frac{l \cdot g}{v_c^2} \sin\alpha\cos\gamma \right), \qquad (22)$$

i.e. an expression of the measured steering wheel angle in terms of vehicle velocity, geometric properties of the road, and vehicle parameters.

4. AN INVARIANT RELATION FOR VDC SENSOR SIGNALS

The geometric information on lateral and longitudinal inclination of the vehicle and the radius of curvature are typically not available within a vehicle dynamic control system. Therefore it is not possible to evaluate the derived sensor equations directly. The idea of the following is to extract an invariant relation from the equations (22), (10), (6) for steering wheel angle sensor, lateral acceleration sensor, and yaw rate sensor that does no more require the geometric properties from the road.

Also the slip angle β is not measured within a standard vehicle. However, one goal of the VDC system is to limit the slip angle at small values (van Zanten *et al.*, 1995). Additionally the slip angle is small for almost all standard driving situations. Thus we follow here the pragmatic approach to consider the slip angle being zero.

With $\beta = 0$ and (10) it is possible to eliminate the term $\sin\alpha \cdot \cos\gamma$ in (22). The remaining complicating term $\frac{\cos\alpha}{\varrho}$ can be eliminated by means of the yaw rate sensor equation (6). The resulting formula

$$\delta_{L,S} = i_L\, l \left(\frac{\omega_{z,S}}{v} + \frac{a_{y,S}}{v_c^2} \right) \qquad (23)$$

is now independent from road information. Provided the assumptions for the measurement equations hold true, this formula is valid for all stationary driving situations characterized by constant CoG velocity v and CoG motion as in (1), i.e. an upward movement in a right turn helix. However, the preceding calculations can be repeated for downward movements and for movements on a left turn helix with only minor changes in the equations for the acceleration and yaw rate sensor.

It turns out that (23) remains unchanged in all these cases (upward/downward driving on right/left turn helices). Especially important in the context of sensor signal monitoring is that (23) is valid for arbitrary ϱ, i.e. also for straight ahead driving, and also for arbitrary longitudinal and lateral inclinations. The usage of (23) in a signal monitoring context is discussed in the next section.

5. CONCEPTUAL MONITORING OF LATERAL DYNAMICS SENSORS IN A VDC SYSTEM

The vehicle velocity v is one of the central signals used within a VDC system. This signal is estimated quite well on the basis of the measured wheel velocities. Together with the measured signals: lateral acceleration $a_{y,s}$, yaw rate $\omega_{z,S}$, and steering wheel angle $\delta_{L,S}$ (and the vehicle parameters l, i_L, v_c) it is possible to monitor deviations from (23) due to sensor failures by means of the residual R_3,

$$R_3 = \delta_{L,S} - i_L\, l \left(\frac{\omega_{z,S}}{v} + \frac{a_{y,S}}{v_c^2} \right). \qquad (24)$$

In the following we briefly outline how a residual-based fault detection scheme substantially can be improved by the additional consideration of the residual introduced by (24).

	R_1	R_2	R_3
$\omega_{z,S}$-failure	0	1	1
$a_{y,S}$-failure	1	1	1
banked curve	1	1	0

Fig. 4. Residual based incidence table.

For simplicity a fault free steering wheel angle sensor and an accurate velocity estimation are assumed. Then it is possible to introduce a fault detection scheme for lateral acceleration sensor and yaw rate sensor with the residuals

$$R_1 = a_{y,S} - \frac{\delta_{L,S}}{i_L \cdot l} \frac{v^2}{1 + \left(\frac{v}{v_c}\right)^2}, \qquad (25)$$

$$R_2 = a_{y,S} - v \cdot \omega_{z,S}, \qquad (26)$$

(derived for stationary driving on a horizontal plane) as decision variables (Börner, 2004; Ding *et al.*, 2004). With the usual single failure assumption a deflection of R_2 indicates a faulty acceleration signal or a faulty yaw rate signal while a non-zero R_1 indicates a faulty acceleration signal. However, the residuals R_1, R_2 will also show a deflection for a banked curve since road geometry is not considered in (25), (26).

This situation is summarized in Figure 4 with the convention that “1” indicates an absolute residual value above a certain threshold (accounting for noise and model uncertainty) and that a “0” indicates the contrary.

It is clear from the left part of Figure 4 that no fault isolation is possible since there is no one-to-one relation between failure and residual pattern. Not even fault detection is possible since driving in a banked curve cannot be distinguished from a lateral acceleration sensor failure.

In practice the residual information is not condensed to $\{0, 1\}$ but also directional information is exploited and ambiguity as e.g. for banked curves can be circumvented by exception handling (Börner, 2004). However, we see that within the simple set-up considered here, only the additional residual information R_3 from the invariant formula (23) is enough to have fault detection *and* isolation. In fact, residual R_3 is sensitive to faulty lateral acceleration signals and to faulty yaw rate signals but not to banked curves. Thus, with the additional information from R_3, the residual patterns in Figure 4 for the three cases considered here become distinguishable.

It is noteworthy that the fault detection and isolation is reached within the residual concept, i.e. as a simple addition of an existing concept without using additional sensors. This is especially important in the context of new centralized concepts for vehicle dynamics sensors in order to cope with complexity of sensor networks in modern vehicles (Rehm and Hofmann, 2004).

6. SUMMARY

In the paper at hand an invariant relation between the core measurement signals of a vehicle dynamics control system is derived. This relation is independent from non-measured geometric information from the road (i.e. radius of curvature, longitudinal- and lateral inclination) and can therefore be incorporated into fault detection and isolation (FDI) schemes. The benefits of using the novel invariant relation in FDI schemes for signal monitoring of vehicle dynamics control systems are outlined by means of a simple incidence based FDI system.

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