

基于云和高斯过程的网联车辆协同式道路参数估计

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摘要: 近年来智能网联汽车发展迅速, 云端预先存储的道路参数信息对于提升网联汽车的悬架控制以及检测路面不规则度至关重要。目前关于道路参数估计的工作大多在单个车辆上完成, 此类算法对于车辆模型不确定性以及测量误差较敏感。针对该问题, 提出了一种新的协同式估计架构, 该架构能够充分利用多个同质的网联汽车的测量信息以提高估计精度。首先, 在云端利用前方行驶的全部车辆的数据对高斯过程模型进行训练以通过众包方式获取道路参数的估计结果。然后, 该结果以未测量的方式发送到后方相邻车辆, 后方单个车辆结合自车车载传感器(如加速度计、横摆角速度以及侧倾角速度)和由云端获取的基于众包高斯过程估计结果, 使用卡尔曼滤波对该估计结果进一步优化。进而估计结果被发送到云端以更新高斯过程模型。大量的仿真实验结果表明, 以该方式使用云端估计的道路参数作为额外的未测量信息能够提高道路参数的估计精度, 验证了该算法的有效性。

关键词: 云端估计; 协同式估计; 道路参数估计; 高斯过程
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Cloud-Based Collaborative Road Profile Estimation Using Gaussian Process

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Abstract: Road profile information is used to improve vehicle suspension control and detect road irregularities such as potholes. While a great many road profile

estimation approaches exist, they have been traditionally performed in a single-vehicle setting, which is inevitably susceptible to vehicle model uncertainty and measurement errors. To overcome these limitations, this paper presents a new collaborative estimation framework that exploits multiple heterogeneous vehicles to iteratively improve the estimation. Specifically, each vehicle combines its onboard measurements (e. g., accelerometers and yaw/roll rate sensors) with a crowdsourced Gaussian process (GP) estimation from the cloud into a Kalman filter (KF) to iteratively refine the estimation. The GP is trained from the crowdsourced local estimations of all prior participating vehicles, which is then sent to the latest participating vehicle as “pseudo-measurements” to enhance the onboard estimation. The resultant local onboard estimation is sent back to the cloud to update the GP. It is shown that using the GP as additional pseudo-measurements can iteratively improve the road profile estimation performance from vehicle by vehicle. Extensive simulations are performed to show the efficacy of the proposed approach.

Key words: cloud-based estimation; collaborative estimation; road profile estimation; Gaussian process

Road profile is one of the most important road characteristics that has been frequently used (or proposed to be used) to improve suspension control^[1-2], enable comfort-based route planning^[3], and alert road agencies for maintenance. Road profilers have been conventionally used to measure road profile. However, they are costly to acquire and maintain and can provide limited coverage. Alternatively, with great advances in vehicular

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telematics, various sensors and communication modules are deployed in modern vehicles, which can potentially be exploited for road profile estimation. Vehicles can thus be used as mobile sensors to crowdsource road information with great road coverage^[4-7].

For instance, vehicle-based estimation approaches have been extensively pursued to exploit the onboard measurements along with the underlying dynamics to reconstruct the road profile^[2, 8-14]. These approaches can be categorized into two classes: unknown input observer (UIO)-based and extended state observer (ESO)-based. The UIO methods generally aim to obtain a precise and stable model inverse to estimate the road profile (which is the input) from the outputs of the system^[8-9]. On the other hand, the ESO methods exploit an augmented state by treating the road disturbance signal as an additional state, which is estimated along with the original states using the commonly used state observers such as the Kalman filter (KF) for linear systems and high gain observers (HGO) or extended KF (EKF) for nonlinear dynamic systems^[2, 10-14].

However, despite the above progresses, these approaches are based on a single-vehicle setting, which is thus susceptible to model uncertainty and measurement errors. To address these challenges, in this paper, a new collaborative estimation framework is developed that exploits multiple heterogeneous vehicles to iteratively improve the estimation. The proposed approach utilizes the cloud as a central platform to crowdsource local vehicle estimations using Gaussian processes (GP)^[15]. The crowdsourced GP is then sent back to the vehicle as a pseudo-measurement to enhance onboard estimation using a KF. The enhanced local estimate is then uploaded to the cloud to update the GP. More specifically, each participating vehicle runs a local KF-based ESO for simultaneous vehicle state and road profile estimation. Instead of just using the available onboard measurements, a crowdsourced “pseudo-measurement” from prior participating vehicle estimates is used to enhance the local estimation. Two types of pseudo-measurements are

considered where in the first case each vehicle uses the previous estimation of the vehicle as the pseudo-measurements whereas in the second case, a trained GP from all prior participating vehicles are used. Both cases are compared with a benchmark to demonstrate the superior performance.

This proposed framework is novel as it systematically exploits the estimates from multiple heterogeneous vehicles to both iteratively enhance onboard estimation and collaboratively refine crowdsourced road profile, through the seamless integration of individual local estimators with the cloud-based Gaussian processes. First, the model dynamics and KF design is introduced. Then, the cloud-based GP regression is investigated whereas the recursive on-board estimation using pseudo-measurements for KF is discussed. Finally, extensive simulation results are expounded.

1 Problem formulation

The aim of this paper is to develop approaches to efficiently crowdsource road profile from multiple heterogeneous vehicles. Specifically, given a road segment (e. g. , defined by two consecutive road mile markers [16]) as illustrated in Fig. 1, the objective of vehicle-based road profile estimation is to use existing onboard sensors (e. g. , accelerometers, GPS, yaw rate, and roll rate) to discover $w(s)$, the road elevation as a function of distance in the longitudinal direction (the s direction in Fig. 1). Here it is assumed that the road profile is uniformly distributed in the lateral direction (v direction in Fig. 1). By scaling the distance s with the vehicle speed, the road profile to be estimated can also be represented by $w(t)$, a function of time. Consider the following dynamics that characterizes the underlying vehicle-road interaction:

$$\begin{aligned} \dot{x}_1 &= x_2 \\ \dot{x}_2 &= \frac{1}{M_s} (-kx_1 - cx_2 + kx_3 + cx_4) \\ \dot{x}_3 &= x_4 \\ \dot{x}_4 &= \frac{1}{M_{as}} (kx_1 + cx_2 - (k + k_t)x_3 - cx_4 + k_t w) \end{aligned} \quad (1)$$

where x_1 , x_2 , x_3 , and x_4 represent the sprung mass

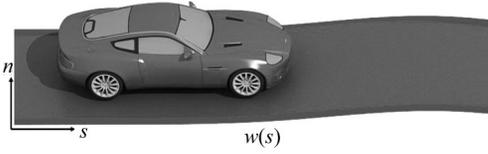


Fig. 1 A road segment with profile denoted by $w(s)$

displacement, sprung mass velocity, unsprung mass displacement, and sprung mass velocity, respectively (see Fig. 2). Here $w \in \mathbf{R}$ is the road disturbance signal, which can be modeled as the output of a low-pass filter whose input is a white Gaussian noise with unit intensity, i. e. $\dot{w} = aw(t) + be(t)$ where a and b are some constants as defined in [17].

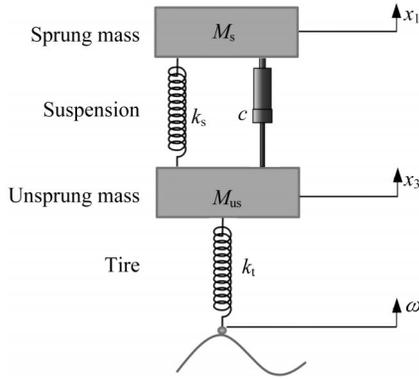


Fig. 2 Illustration of a quarter-car suspension model

Thus, by augmenting the road signal w as an additional state, i. e., Eq. (1) can be rewritten into the following augmented state-space model

$$\begin{aligned} \bar{x}(k+1) &= A\bar{x}(k) + G\eta(t) \\ \mathbf{y}(k) &= C\bar{x}(k) + v(k) \end{aligned} \quad (2)$$

where A , G , and C are appropriate matrices derived from Eq. (1); η is the white Gaussian noise; and \mathbf{y} is the noisy output measurements. Discretizing the system with an appropriate sampling time yields the following discrete state space equations:

$$\begin{aligned} \bar{x}(k+1) &= A_d\bar{x}(k) + G_d\eta(k) \\ \mathbf{y}(k) &= C\bar{x}(k) + v(k) \end{aligned} \quad (3)$$

which can now be used in a KF to estimate the augmented state which includes the road disturbance signal by the following two steps:

Prediction:

$$\begin{aligned} \hat{\bar{x}}(k|k-1) &= A_d\hat{\bar{x}}(k-1|k-1) \\ P(k|k-1) &= A_dP(k-1|k-1)A_d^T + G_dQG_d^T \end{aligned}$$

Correction:

$$\begin{aligned} \Gamma(k) &= P(k|k)C^T[CP(k|k-1)C^T + R]^{-1} \\ \hat{\bar{x}}(k|k) &= \hat{\bar{x}}(k-1|k-1) + \Gamma(k)[\mathbf{y}(k) - \end{aligned}$$

$$C\hat{\bar{x}}(k-1|k-1)]$$

$$P(k|k) = [I - \Gamma(k)C]P(k|k-1) \quad (4)$$

The above description is a standard ESO design and will serve as a benchmark to compare with the developed collaborative estimation method which will be discussed next.

2 Cloud-based Gaussian process regression

In Section 2, road profile estimation with a single vehicle using ESO is presented. In this section, a cloud-based collaborative estimation framework is developed to iteratively refine the estimates from single vehicles. The considered GP-based collaborative road profile estimation framework is illustrated in Fig. 3. Specifically, each participating vehicle i receives a Gaussian process (GP) $GP_{i-1}(m_{i-1}(s), K_{i-1}(s, s') | \hat{\Theta}_{i-1})$ with a mean function $m_{i-1}(s)$ and a kernel function $K_{i-1}(s, s')$ parameterized by $\hat{\Theta}_{i-1}$, from the cloud.

The GP model describes the road profile distribution (with both mean and covariance), aggregated from the data of prior participating vehicles until vehicle $i-1$. The received $GP_{i-1}(\cdot, \cdot | \Theta_{i-1})$ is then utilized as a priori “pseudo-measurement” of the road profile, forming an augmented output along with the onboard measurements as $\bar{\mathbf{y}} = [\mathbf{y}; \hat{\mathbf{w}}_{i-1}]$, where $\hat{\mathbf{w}}_{i-1} \sim GP_{i-1}(\cdot, \cdot | \Theta_{i-1})$. This augmented output is then incorporated into a local estimator (e. g., KF or JDP-based estimator) to estimate the augmented state (both vehicle state and road profile). This GP “pseudo-measurement” can be viewed as an additional sensor measurement, providing both the means and the covariances of the road profile to be fused with onboard sensors for enhancing the local estimation. The pair of road profile and position estimate sequence, $(\hat{\mathbf{w}}_i, \hat{\mathbf{s}}_i) := \{\hat{\mathbf{w}}_i, \hat{\mathbf{s}}_i\}_{i=1}^N$ is then uploaded to the cloud to update the GP hyper-parameters using e. g., maximum likelihood learning:

$$\begin{aligned} \hat{\Theta}_i &= \arg \max_{\Theta} \text{Prob}(\hat{\mathbf{w}}_1(\hat{\mathbf{s}}_1), \hat{\mathbf{w}}_2(\hat{\mathbf{s}}_2), \dots, \\ &\quad \hat{\mathbf{w}}_i(\hat{\mathbf{s}}_i) | \hat{\mathbf{s}}_1, \hat{\mathbf{s}}_2, \dots, \hat{\mathbf{s}}_i, \Theta) \end{aligned} \quad (5)$$

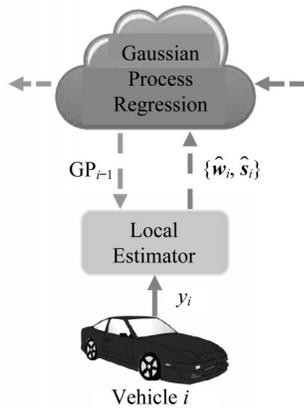


Fig. 3 Schematics of collaborative estimation using GP

The updated GP with hyper-parameters $\hat{\Theta}_i$, $GP_i(\bullet, \bullet | \Theta_i)$ is then sent to the next participating vehicle $i+1$ to enhance its estimate. The process is then repeated.

In the presented framework, N number of vehicles are considered which can collaboratively improve the estimation of the road disturbance signal from vehicle to vehicle. When Vehicle i passes the considered road segment, it will pass its KF estimation information of the road disturbance signal to the cloud which has the capability of storing large data structures and dealing with heavy computations. On the cloud side, the road profile estimations of Vehicle i and all prior participating vehicles are used to fit a GP to characterize the road disturbance. The goal is that as more vehicles collaborate in the proposed estimation framework, the estimation error for the cloud-based GP and for the vehicle on-board estimation is reduced. Next, more details are provided regarding the GP and the collaborative estimation framework.

The road profile can be described by a function of the spatial distance, $w(s)$, or characterized by its power spectrum density^[18]. An alternative description is from a machine learning perspective using the GP model [19], i. e., $w(s) \sim GP(m(s), k(s, s'))$, where $m(s) = E[w(s)]$ is the mean function that can take the form of $m(s) = \sum_{j=1}^K \beta_j \psi_j(s) = \beta^T \psi(s)$, where $\psi(\cdot)$ is the vector of K basis functions (e. g., polynomial functions or

Gaussian basis functions), and β is the vector of corresponding linear weights to be trained from the data. The kernel function, $k(s, s') = Cov(s, s')$, characterizes the covariance between any two spatial points s and s' , an example of which is the exponentiated quadratic kernel $k(s, s') = \sigma^2 \exp\left(-\frac{\|s - s'\|^2}{2l^2}\right)$, where σ and l are the hyper-parameters

representing the standard deviation and the length scale, respectively. The set of hyper-parameters from the mean function and the kernel function (e. g., $\Theta = \{\beta, \sigma, l\}$ are denoted by Θ for the above example functions). This GP representation of road profile is advantageous as it not only provides an estimated profile (i. e., the mean function) but also the estimation uncertainties characterized by the kernel function.

In this paper, GP is used to predict and update the spatial function values of the road disturbance signal for a considered road segment. More specifically, Vehicle i passes the considered road segment and sends its KF estimation points $\{\hat{s}_i, \hat{w}_i\}_{i=1}^N$ to the cloud, where (\hat{s}_i, \hat{w}_i) is the sequence of the estimated road signal points. Gathering all the estimated values for the road signal up to Vehicle i , the training data points for the cloud-based GP will be $D = \{(\hat{s}_1, \hat{w}_1), (\hat{s}_2, \hat{w}_2), \dots, (\hat{s}_i, \hat{w}_i)\}$. In this regard, the input and output training data matrices can be written by stacking the data points obtained by each KF for Vehicle 1 to Vehicle i as $\hat{S} = [\hat{s}_1, \hat{s}_2, \dots, \hat{s}_i]$ and $\hat{W} = [\hat{w}_1, \hat{w}_2, \dots, \hat{w}_i]$ respectively. The objective is to approximate the nonlinear mapping of a system

$$w_s = f(s) + \epsilon \quad (6)$$

with white additive Gaussian noise $\epsilon \sim N(0, \sigma_\epsilon^2)$. Given a GP prior, it follows that the output data is a related normal distribution

$$\hat{W} \sim N(0, K + \sigma_\epsilon^2 I) \quad (7)$$

With the tuned hyperparameters of the kernel and mean function, predictions can be made by posterior

inference conditional on observed data D . Using these information, the predictive equations for the i th GP regression at points s_* follow as

$$\mathbf{w}_{GP,i} = E[\mathbf{w}_* | \hat{\mathbf{S}}, \hat{\mathbf{W}}, s_*] = K(s_*, \hat{\mathbf{S}}) [K(\hat{\mathbf{S}}, \hat{\mathbf{S}}) + \sigma_\epsilon^2 I]^{-1} \hat{\mathbf{W}} \quad (8)$$

$$\text{Cov}(\mathbf{w}_{GP,i}) = K(s_*, s_*) - K(s_*, \hat{\mathbf{S}}) \times [K(\hat{\mathbf{S}}, \hat{\mathbf{S}}) + \sigma_\epsilon^2 I]^{-1} K(\hat{\mathbf{S}}, s_*) \quad (9)$$

The proposed cloud-facilitated collaborative estimation with GP has several advantages. First, it works for heterogeneous vehicles as the framework has no requirement in vehicle homogeneity. Each vehicle exploits its own model and an estimator for local estimation. Second, the ‘‘pseudo-measurement’’ scheme is guaranteed to reduce the estimation variance from iteration to iteration thanks to the posterior covariance reduction update in KF^[20]. Finally, as the only information regarding road estimate is communicated, privacy-sensitive information such as vehicle states are inherently protected. The GP crowdsources the estimates from multiple vehicles to iteratively improve the road profile estimation, which is then shared with participating vehicles to enhance its onboard state and road estimation.

3 Cloud-assisted onboard estimation with pseudo-measurements

In this section, the idea of pseudo-measurement from the cloud as an additional measurement is presented to enhance the local estimation performance. In particular, two types of pseudo-measurements are considered. The first is to use the KF from the last vehicle as the pseudo-measurement while the second is to use the crowdsourced GP as the pseudo-measurement.

3.1 KF pseudo-measurements

When Vehicle i passes a road segment, the KF for Vehicle i uses the KF estimation of Vehicle $i-1$ as extra measurements i. e., the output y for Vehicle i will be modified as

$$\bar{\mathbf{y}}_i(k) = \begin{bmatrix} C\bar{x}_i(k) + v_i(k) \\ \hat{w}_{i-1}(k) \end{bmatrix}$$

The modification of the output of the KF for Vehicle i results in the modification of the KF algorithm as well. That is, a new measurement noise covariance for Vehicle i is defined by taking account of the variance of the road signal estimation error of the prior Vehicle $i-1$ at each time step. This can be formulated as a KF with augmented pseudo-measurements as

Prediction:

$$\bar{x}_i(k|k-1) = A_d \bar{x}_i(k-1|k-1)$$

$$P_i(k|k-1) = A_d P_i(k-1|k-1) A_d^T + G_d Q_i G_d^T$$

Correction:

$$\Gamma_i(k) = P_i(k|k) \bar{C}_i^T [\bar{C}_i P_i(k|k-1) \bar{C}_i^T + \bar{R}_i(k)]^{-1}$$

$$\bar{x}_i(k|k) = \bar{x}_i(k-1|k-1) + \Gamma_i(k) [\mathbf{y}_i(k) - \bar{C}_i \bar{x}_i(k-1|k-1)]$$

$$P_i(k|k) = [I - \Gamma_i(k) \bar{C}] P_i(k|k-1) \quad (10)$$

where \bar{C} and \bar{R} are the modified output matrix and modified measurement noise matrix respectively, i. e.

$$\bar{C} = \begin{bmatrix} C & & & \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}, \bar{R}(k) = \begin{bmatrix} R & 0 \\ 0 & \sigma_{w_{i-1}}^2(k) \end{bmatrix}$$

and $\sigma_{w_{i-1}}^2(k)$ stands for the variance of the road disturbance signal estimation error of the KF for Vehicle $i-1$ at the time step k . This recursive scheme will lead to a better estimation of the road profile as each vehicle travels the road segment as shown in the simulations.

3.2 GP pseudo-measurements

In this case, the KF for each vehicle will incorporate the information of the latest GP regression as the pseudo-measurements for the road profile estimation purpose. Specifically, the output measurement for Vehicle i is modified as

$$\bar{\mathbf{y}}_i(k) = \begin{bmatrix} C\bar{x}_i(k) + v_i(k) \\ \hat{w}_{GP,i-1}(k) \end{bmatrix}$$

Similarly, the KF for Vehicle i will be augmented with GP pseudo-measurements as the previous case, where \bar{R} in this case is equal to

$$\bar{R}(k) = \begin{bmatrix} R & 0 \\ 0 & \text{VAR}(\mathbf{w}_{GP,i-1}(k)) \end{bmatrix}$$

where $\text{VAR}(\mathbf{w}_{GP,i-1}(k))$ stands for the variance of the road disturbance signal estimation error obtained by

the latest GP regression done at the cloud at iteration number $i - 1$. In Section 5, how these two types of extra measurements will lead to better performance of the on-board KFs in each vehicle will be demonstrated. It is noted that the proposed framework will still work if a nonlinear plant model is used. In this case, instead of using KFs, nonlinear observers such as EKFs and high-gain observers can be used for local estimations.

4 Simulation

In this section, simulation results for the proposed collaborative estimation framework are presented. Specifically, $N=5$ heterogeneous vehicles with different model parameters are considered. The parameter values for constructing the A and G matrices in Eq. (2) for each vehicle $i=1, \dots, N$ are

$$\begin{aligned} M_s &= 300 \times \left(\frac{90+i}{100} \right) \text{kg}, i=1, \dots, N, \\ M_{us} &= 60 \text{kg} \\ c &= 1000 \frac{Ns}{m} \\ k_{s,i} &= 16000 \times \left(\frac{90+i}{100} \right) \frac{N}{m}, \\ i &= 1, \dots, N, k_t = 190000 \frac{N}{m} \\ a &= -0.01, b = 0.0328 \end{aligned}$$

where the C matrix is also chosen as

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & -1 & 0 & 0 \end{bmatrix}$$

which corresponds to the measurements of sprung mass displacement and suspension deflection that are available in (semi-)active suspension systems.

In the simulations, all participating vehicles travel through a road segment of 5m in length at the same speed. This results in the correspondence of the estimated points of each vehicle obtained by the KF algorithm. The actual road profile was generated based on a Class-C road^[17]. The measurement noise v_i for each vehicle is generated in a way that the signal-to-noise ratio is between 10 and 20. For the cloud-based GP, the initial GP prior is defined with a zero mean function and squared exponential (SE)

covariance function, i. e.

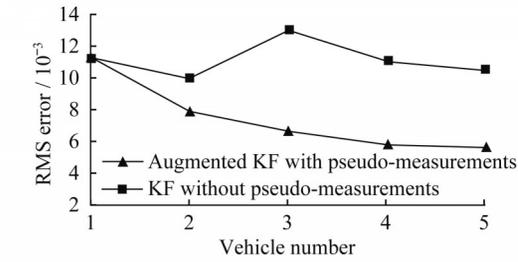
$$K(s_i, s_j) = \sigma_f^2 \exp\left(-\frac{r^2}{2l^2}\right) \quad (11)$$

In this equation, the hyperparameter σ_f^2 stands for the signal variance or the vertical scaling factor whereas the hyperparameter l is known as the horizontal scaling factor. In other words, the distance that is needed to move along the specified axis in the input space so that the function values become uncorrelated^[21]. The parameter r is the distance measure of the inputs and equals to $r = |s_i - s_j|$ ^[22].

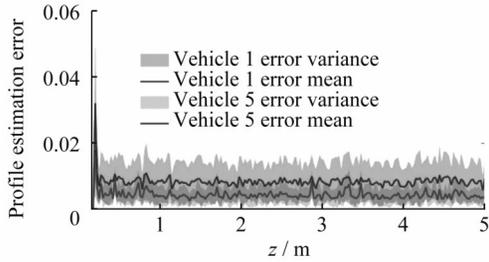
For the GP regressions, there are 3 approaches to calculate Eqs. (8) and (9). The first approach is that, for the i th GP, all the estimation data of the KF up to vehicle number i is used as the training points and then the posterior is inferred given all the collected data. The second approach is to similarly collect all the data up to Vehicle i but instead use a sparsity approximation GP approach. The last one is to use an updating recursive approach^[6] where for the new arriving data, the GP will infer the posterior distribution given all the previous data without taking account of all the collected data to construct the matrices in Eqs. (8) and (9) which will cause a heavy computational burden if there are a lot of training data points. In this preliminary study, the first approach is used as the number of considered vehicles are small and the implemented approach does not impose heavy computational burden. Other approaches will be considered in the future.

The performance of the proposed recursive KF for Vehicles 1 to 5 when exploiting the KF pseudo-measurements from the prior vehicle is compared with the benchmark case, i. e., without using the pseudo-measurements. The results are shown in Figure 4a and it is clear that using this extra measurement can reduce the root mean squared error (RMSE) of the estimated road profile. This extra measurement is helpful for the KF algorithm to have a better estimation in general and the variances of the estimation error decreases from vehicle to vehicle. Fig. 4b shows the mean and variance of the road profile estimation error when comparing Vehicles 1 and 5, which shows that a lower mean and variance is

achieved in the last vehicle (Vehicle 5) as compared to the Vehicle 1.



a RMSE of the on-board KF of the vehicle with respect to the actual road with and without using pseudo-measurements



b mean and variance of the estimation error at each road profile coordinate

Fig.4 Onboard estimation performance estimation

Fig. 5 - Fig. 7 summarizes the performance of the proposed recursive KF when exploiting the latest GP pseudo-measurements as pseudo-measurements. Fig. 5 is a comparison of the GP pseudo-measurement case and the benchmark setting where each vehicle performs the KF without using the pseudo-measurements. It is clearly observed that using pseudo-measurements brings about a superior performance. For the KF using pseudo-measurements, after Vehicle 4 the error does not decrease much. This is due to the fact that after certain number of vehicles, the GP will fit a curve to the road profile which has a low variance and the next KF (that is, the KF for Vehicle 5 which uses the GP pseudo-measurement) will be more likely to trust the latest GP pseudo-measurement rather than the process dynamics. Going one step before, on the GP side, this is the result of using the training data points originated from the previous KFs augmented with GP pseudo-measurements. This iterative use of the information of GP for the KF estimation of road profile and the use of GP of the estimation of KF, is the reason that eventually both KF and GP predictions converge to a single road profile and the improvement will be halted. Ongoing research is on the development of new ideas to enhance

the current result.

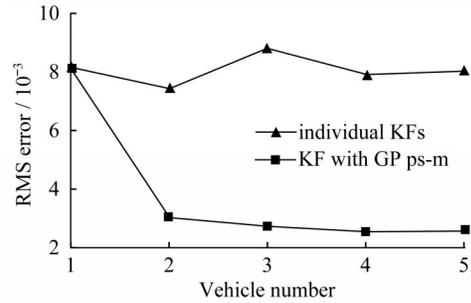


Fig. 5 RMSE of the on-board KF of the vehicle with respect to the actual road with and without using pseudo-measurements

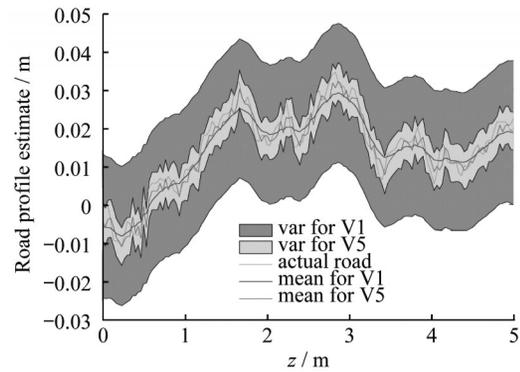


Fig. 6 First and last GP regression

Fig. 6 is a comparison of the first cloud-based GP regression and the last one. In addition to reduction of the variance from the first to the last vehicle, the improvement of the mean function, which is the prediction of the GP of the road profile, is significant. In Fig. 7, the cloud based RMSE of the GP regression with the actual road profile for GP fit number i is compared with the average of KFs up to Vehicle i , used as a benchmark. The results show a clear superiority of the GP regression, resulting in a lower RMSE of road profile for all vehicles.

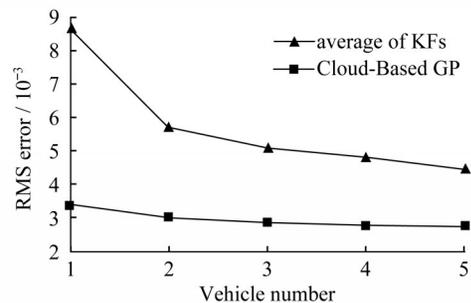


Fig. 7 Comparison of the cloud-based GP and the benchmark setting

5 Conclusion

In this paper, a novel cloud-based collaborative road profile estimation framework using multiple heterogeneous vehicles was developed. GP was used to crowdsource individual estimates, which was then used as pseudo-measurements for future vehicles to enhance its local measurements. This pseudo-measurement was able to greatly enhance the local estimation performance. The enhanced local estimation was then uploaded to the cloud to update the GP estimation. Future work will focus on dealing with GPS imprecision and data-efficient GP to make this framework more practically viable.

作者贡献声明:

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HAJIDAVALLOO MOHAMMAD R: Formal analysis, Software, Writing original draft.

XIA Xin: Discussion, Writing-review & editing.

ZHENG Minghui: Discussion, Writing-review & editing.

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