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AUTOMATED ROAD PROFILE ESTIMATION BY SMARTPHONE ON BICYCLE DATA

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1. INTRODUCTION

The importance of bicycle transportation in Japan has been rapidly increasing and the development of bicycle paths has been progressing rapidly in recent years. Also, the demand for bicycle transportation is expected to further increase in the future. On the other hand, the evaluation of paved road surfaces is left to visual inspection by patrol vehicles, and there is currently no quantitative monitoring and evaluation method for bicycle paths, despite the vast amount of space for bicycle travel. From the inspection's point of view, it is expected that short-wavelength deformations such as cracks and potholes can be identified in order to prevent accidents and avoid liability for defects in management. Furthermore, from the bicycle rider's point of view, it is required to improve not only safety but also ride comfort.

Keeping these perspectives in mind, the first study of road profile estimation based on a smartphone on a bicycle was done by Yamaguchi et al. (2019). The Kalman filter was used to estimate the road profile by combining two sensor data, i.e., vertical acceleration and pitching angular velocity collected by the smartphone. The method could obtain an estimation of pavement profile assuming the traveling speed constant in wideband spectrum. The correlation between the estimated road profile and the road profiler measurement is as accurate as .81 and the max IRI error was 14%. However, assuming traveling speed constant would be unrealistic. Furthermore, the process and observation noise in the Kalman filter must be tuned manually for different profiles and speeds. In this study, a stochastic Robbins-Monro algorithm (1951) is implemented to overcome this shortcoming and adaptively set the process and measurement noise covariance matrices. And the instantaneous speed of the bicycle was fed to the Kalman filter, which adds nonlinearity.

2. ESTIMATION ALGORITHM

2.1 Sensor fusion by Kalman filter

To estimate the profile, sensor fusion is utilized to combine the acceleration and angular velocity data. In this process, the errors between the estimated profile and pitch of the bicycle and the true profile and pitch are minimized. e_{ya} is the difference between the true profile and the profile estimated by integrating twice the vertical acceleration. e_{va} is the difference between the true vertical velocity and the vertical estimated by integrating once the vertical acceleration. $e_{y\theta}$ is the difference between the true profile and the profile estimated by pitch. $e_{\theta w}$ is the difference between the true pitch and the pitch estimated by the angular velocity w. $e_{\theta g}$ is the difference between the true gravity acceleration and the measured gravity acceleration. The equation of the state of the Kalman filter is represented in Eq. (1). In the previous study the term Δx was calculated by ΔtV in Eq. (1). Where V is constant traveling velocity. In the current study, Δx is calculated by $\Delta t v(t)$. Where $v(t)$ is instantaneous traveling velocity and Δt is the sensor measurement time interval. This change in the state equation introduces nonlinearity in the Kalman filter.

$$\begin{bmatrix} e_{ya}(t_n) \\ e_{va}(t_n) \\ e_{y\theta}(t_n) \\ e_{\theta w}(t_n) \\ e_{\theta g}(t_n) \end{bmatrix} = \begin{bmatrix} 1 & \Delta t & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & \Delta x & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} e_{ya}(t_{n-1}) \\ e_{va}(t_{n-1}) \\ e_{y\theta}(t_{n-1}) \\ e_{\theta w}(t_{n-1}) \\ e_{\theta g}(t_{n-1}) \end{bmatrix} + \begin{bmatrix} 0 & 0 & 0 \\ \Delta t & 0 & 0 \\ 0 & 0 & 0 \\ 0 & \Delta t & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} n_a(t_n) \\ n_w(t_n) \\ n_g(t_n) \end{bmatrix} \quad (1)$$

Where n_a, n_w and n_g are the normal white noise of acceleration, angular velocity and gravity respectively (process noise). The observables are the difference E_y, estimated from e_{ya} and $e_{y\theta}$ and the difference E_θ, estimated from $e_{\theta w}$ and $e_{\theta g}$. Thus, the observation equation becomes (Eq. (2)):

$$\begin{bmatrix} E_y(t_n) \\ E_\theta(t_n) \end{bmatrix} = \begin{bmatrix} 1 & 0 & -1 & 0 & 0 \\ 0 & 0 & 0 & 1 & -1 \end{bmatrix} \begin{bmatrix} e_{ya}(t_n) \\ e_{va}(t_n) \\ e_{y\theta}(t_n) \\ e_{\theta w}(t_n) \\ e_{\theta g}(t_n) \end{bmatrix} + v \quad (2)$$

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The covariance matrix of n_a, n_w and n_g are defined as in Eq. (3):

$$E[nn^T] = Q_k \\ E[vv^T] = R_k \tag{3}$$

Where v is observation noise and Q_k and R_k are diagonal matrix.

2.2 Robbins-Monro algorithm

The performance of the Kalman filter is affected by the covariance matrices for process (Q_k) as well as observation noise (R_k). In addition, process and measurement noises may not always remain constant with time. Consequently, a method is required to automatically modify the covariance matrices. The Robbins-Monro algorithm can adaptively set Q_k and $R_k$matrices based on the state vector and observation variables (Eq. (4)).

$$Q_k = (1-\alpha_Q)Q_{k-1} + \alpha_Q G_k (E_k - E_k^-)(E_k - E_k^-)^T G_k^T \; R_k \\ = (1-\alpha_R)R_{k-1} + \alpha_Q (E_k - E_k^-)(E_k - E_k^-)^T \tag{4}$$

Where G_k is Kalman gain and α_Q and α_R are two forgetting parameters of Robbins-Morno algorithm. Inaccurate parameters may lead to divergence, instability, or convergence toward erroneous values.

4. Numerical Verification

Both the algorithm of previous and current study is tested on a road based at the campus for various travelling speeds is shown in Fig. 1 and Fig. 2. The distance analyzed is around 80m. The actual IRI is measured through hand pushed DAM. Before applying the algorithm, the measurements have been preprocessed by resampling and filtering.

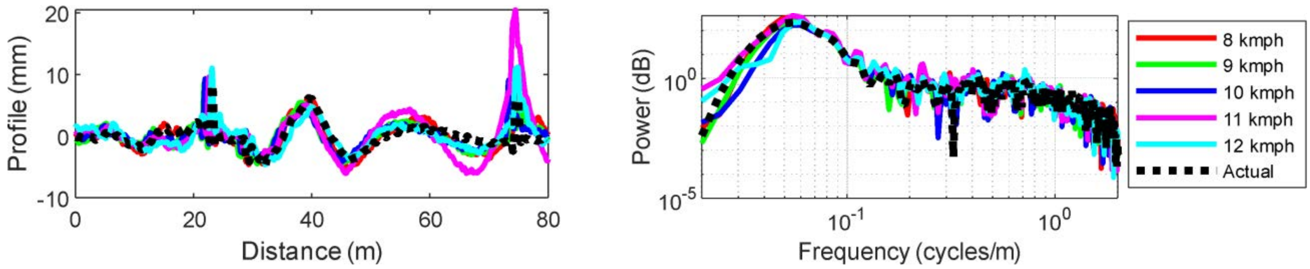

Fig. 1 Results obtained by Yamaguchi et al. (2019) (a) Profile (b) PSD of profile.

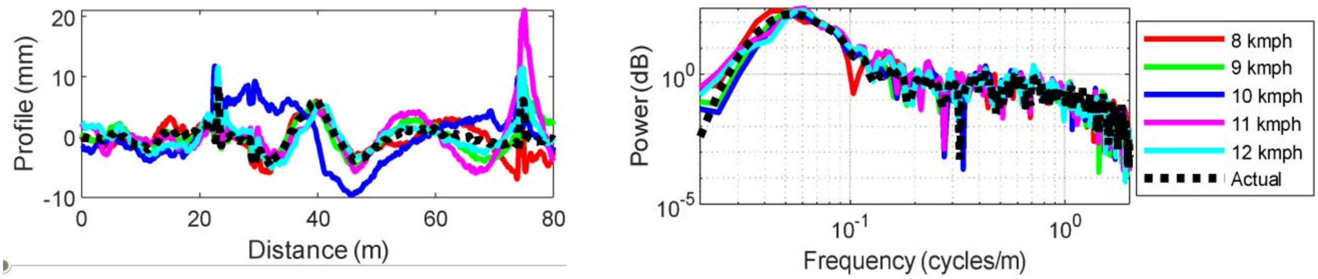

Fig. 2 Results obtained by current study (a) Profile (b) PSD of profile.

For the current study the initial guess for the Q_k and R_k are arbitrarily set. Which is advantageous over the previous study. The estimations obtained from the current study performed very well. However, the profile estimate of 8kmph and 10kmph looks worse than the profile estimated in the previous study. One possible reason for this can be the bad choice of parameters in the Robbins-Monro algorithm. The other estimation looks satisfactory. In this bandwidth detecting short-wavelength deformations such as cracks and potholes was accurate.

5. CONCLUSIONS

Robbins-Monro algorithm has its own parameter. The choice of the parameter can lead to the approximation of the $Q_k$and R_k to converging or diverging or unstable. So, it's essential to choose the parameter correctly. Also, the initial guess for the $Q_k$and R_k in the Robbins-Morno should be close to the actual value. The process of automating the choice of Robins-Morno parameter is unclear. Further study has to be conducted.

REFERENCES

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