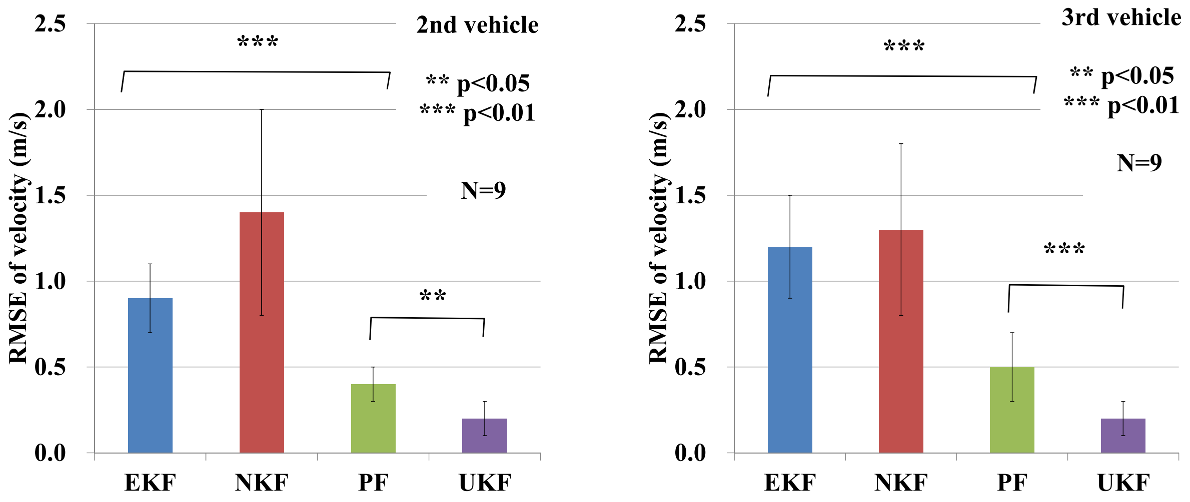

Figure 6. RMSE of velocity estimations (measuring acceleration only)

The estimate by the NKF is the worst for all state variables among the four estimators because the NKF is still sensitive to the parameters of the ANN. As shown in Table 2, however, the NKF outputs better estimates than the EKF in some scenarios for headway estimations. Although the NKF does not always yield inaccurate estimates, the NKF is more difficult to handle than the PF and UKF due to sensitivity to the parameters of the ANN.

Table 2. RMSE of all state variables for artificial nine scenarios (AS1~AS9).

RMSE of headway (m) (2nd vehicle)				
	EKF	NKF	PF	UKF
AS1	3.3	1.3	0.6	0.6
AS2	3.1	2.6	2.0	0.6
AS3	1.2	2.7	1.3	1.3
AS4	2.5	7.1	1.4	1.5
AS5	1.1	4.2	1.0	0.7
AS6	1.7	17.2	1.6	0.7
AS7	0.6	19.9	1.0	0.5
AS8	2.9	6.8	1.4	0.9
AS9	1.5	3.2	1.4	0.8
mean	2.0	7.2	1.3	0.8
S.D	1.0	6.7	0.4	0.3

RMSE of velocity (m/s) (2nd vehicle)				
	EKF	NKF	PF	UKF
AS1	1.4	0.5	0.4	0.1
AS2	1.0	1.1	0.4	0.1
AS3	0.7	0.7	0.5	0.3
AS4	1.0	1.9	0.2	0.3
AS5	0.8	1.5	0.2	0.1
AS6	0.9	1.4	0.4	0.1
AS7	0.9	2.3	0.4	0.1
AS8	0.6	1.5	0.5	0.2
AS9	0.9	1.5	0.4	0.2
mean	0.9	1.4	0.4	0.2
S.D	0.2	0.6	0.1	0.1

RMSE of headway (m) (3rd vehicle)				
	EKF	NKF	PF	UKF
AS1	4.8	0.8	0.7	0.3
AS2	2.9	1.8	0.7	0.2
AS3	1.5	1.5	1.1	0.3
AS4	2.5	1.3	1.3	1.1
AS5	4.1	4.6	0.9	0.2
AS6	4.9	1.7	0.5	0.2
AS7	3.8	7.6	1.4	0.3
AS8	5.9	2.5	0.9	0.3
AS9	3.6	19.2	0.7	0.2
mean	3.8	4.6	0.9	0.3
S.D	1.3	5.9	0.3	0.3

RMSE of velocity (m/s) (3rd vehicle)				
	EKF	NKF	PF	UKF
AS1	0.8	0.6	0.8	0.1
AS2	1.0	1.1	0.4	0.1
AS3	1.0	0.8	0.6	0.3
AS4	1.3	1.8	0.3	0.4
AS5	1.8	1.7	0.2	0.2
AS6	0.8	1.1	0.4	0.1
AS7	1.4	1.9	0.5	0.1
AS8	1.1	1.4	0.7	0.2
AS9	1.2	1.6	0.5	0.2
mean	1.2	1.3	0.5	0.2
S.D	0.3	0.5	0.2	0.1

4.4 Estimation Results by Measuring both Acceleration and Velocity

The previous analysis showed that the PF and UKF provide the best performance among the four estimators, so that only the PF and UKF are accepted in the estimation where the velocity of a probe car is also chosen as a measurement variable in addition to the acceleration rate. The data sets and scenarios are the same as the analysis described in Section 4.1.

As an example out of nine scenarios, the performance of the PF and UKF in scenario AS9 is illustrated in Figures 7 and 8 in comparison with the case where no filter is applied. The superior performance of the PF and UKF are visible. Inaccurate estimate is observed in the no-filter case especially when estimating the headway distance of both the second and third vehicles. In contrast, The PF and UKF succeeded in minimizing the errors through the filtering process using the multiple particles and sigma points generated for those estimators.

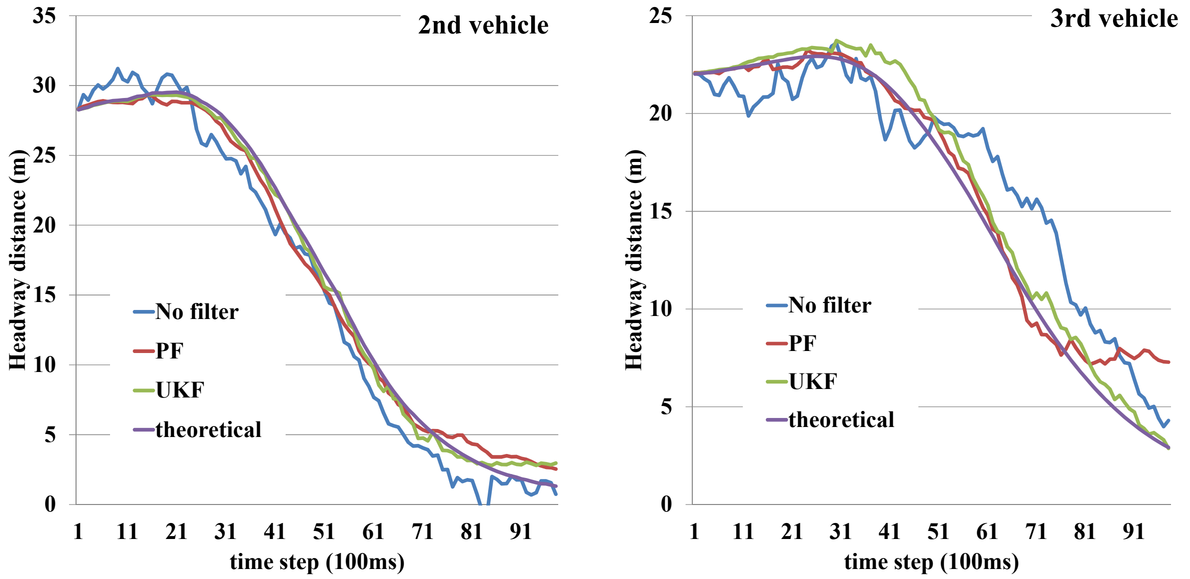

Figure 7. Estimates of the headway distance in scenario AS9 (measuring acceleration and velocity)

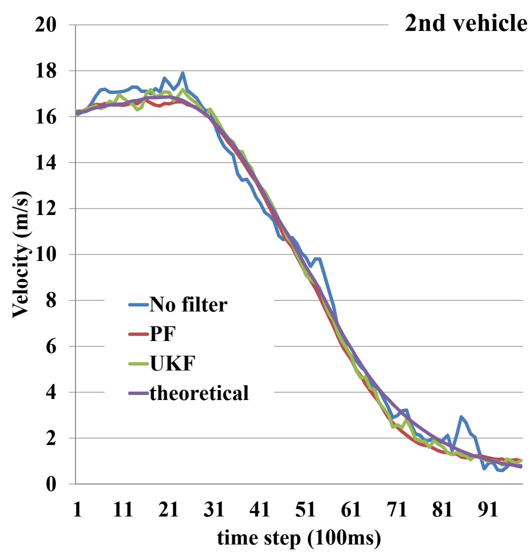

Figure 8. Estimates of the velocity in scenario AS9 (measuring acceleration and velocity)

The error statistics of headway and velocity estimations are depicted in Figures 9 and 10. The PF and UKF statistically show higher precision than the no-filter case at more than 1 % confidence level. Also, their variance of the errors are much smaller than the no-filter case. That is, both the PF and UKF had consistency lower errors with no statistical difference observed between them despite the UKF showing statistically higher accuracy than the PF in the case of measuring acceleration only. The better performance of the PF and UKF is still clear when using both acceleration rate and velocity as measurement variables. Note that one scenario of the UKF is excluded from the statistics due to an unexpected computation error in scenario AS5. It has not been confirmed, but it seems that the UKF may yield a slightly larger error when treating a state variable as also a measurement variable (i.e. the velocity of the third vehicle is a state variable to be estimated as well as a measurement variable).

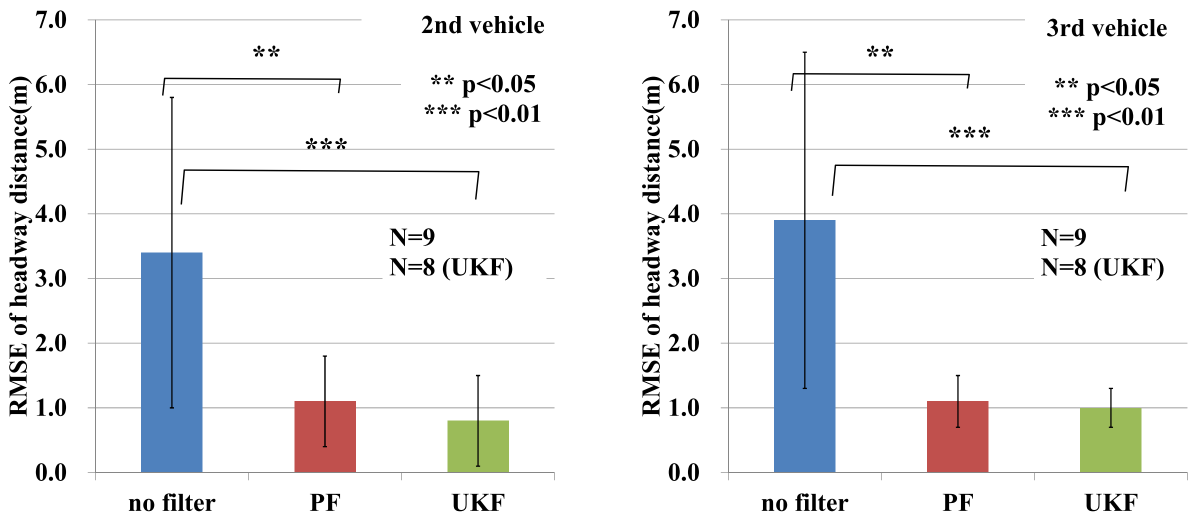

Figure 9. RMSE of headway distance estimations (measuring acceleration and velocity)

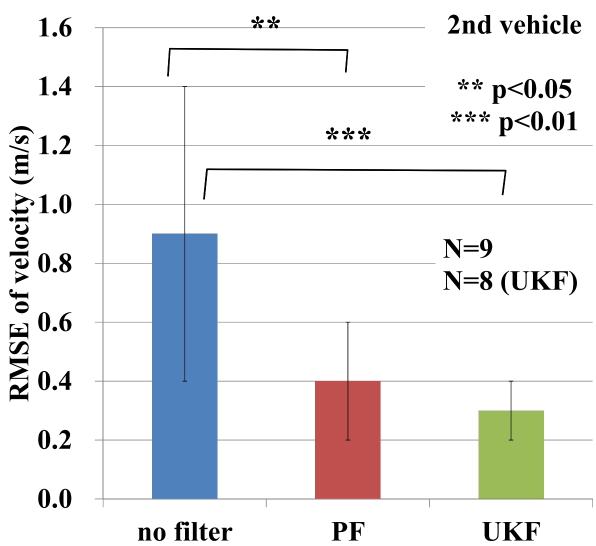

Figure 10. RMSE of velocity estimation (measuring acceleration and velocity)

5. Numerical Analysis Using Real Car-Following Data

5.1 Preparing Real Car-Following Data Set

Real car-following data including headway distance, velocity and acceleration rate of three vehicles were collected in a field test using a test truck of the Japan Automobile Research Institute (JARI). In the test, a three-vehicle platoon travelling at a steady speed of around 60 km/h was made to decelerate and come to a complete stop, and this process was repeated. The deceleration rate was random from 1 to 5 m/s^2. Thirteen real-data scenarios (RS1 to RS13) which are suitable for the analysis were selected and used for the evaluation.

5.2 Estimation Results by Measuring Acceleration Only

As an example out of thirteen scenarios, Figures 11 and 12 compare the headway and velocity estimates of scenario RS4 among two estimators, PF,UKF and no-filter case. The statement "observed" in the legend means the real observed headway distance or velocity to be compared. PF and UKF yield more accurate estimates than no-filter case for all state variables. Especially in the headway estimation of 2nd and 3rd vehicles, PF and NKF reduced the unexpected under estimation that was seen in no-filter case.

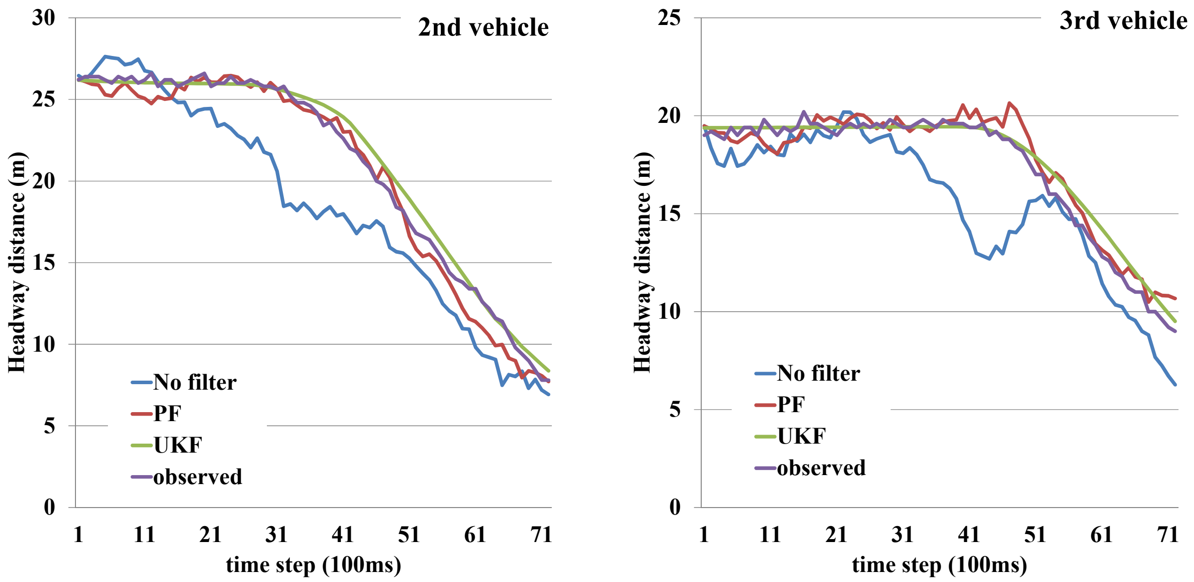

Figure 11. Estimates of headway distance in scenario RS4 (measuring acceleration only)

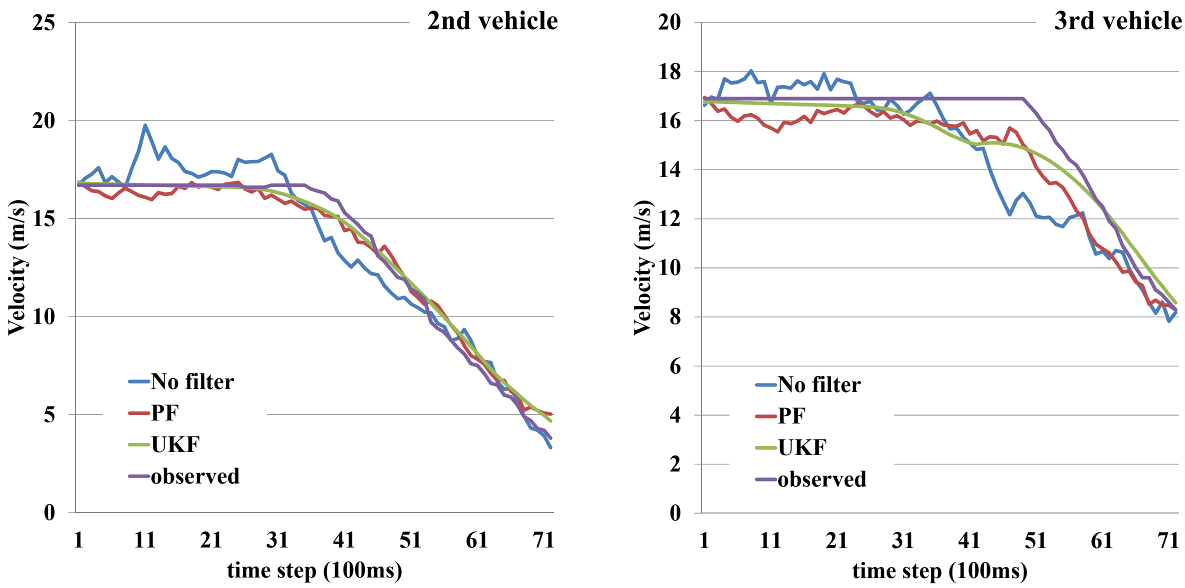

Figure 12. Estimates of velocity in scenario RS4 (measuring acceleration only)

Figures 13 and 14 depict the mean and standard deviation of root mean square errors (RMSE) of four state variables among thirteen scenarios. The t-test showed that mean errors of both headway estimates are statistically smaller than the no-filter case at 1% confidence level. The absolute error around 1 m, which is equivalent to the error by laser radar, is also acceptable as the satisfactorily level.

In the velocity estimations, however, no statistical difference is observed except the PF in the velocity estimates of 2nd vehicle although PF and UKF seem to decrease the mean errors. But, the absolute mean error around 0.8 to 1.2 m/s can be considered as the acceptable level for the collision risk evaluation.

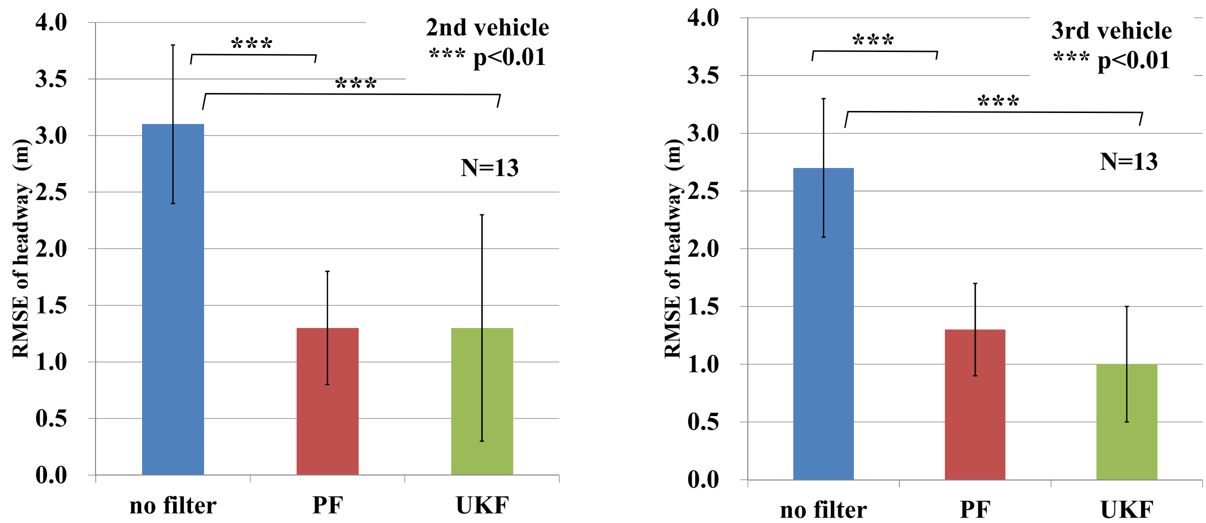

Figure 13. RMSE of headway distance estimations (measuring acceleration only)

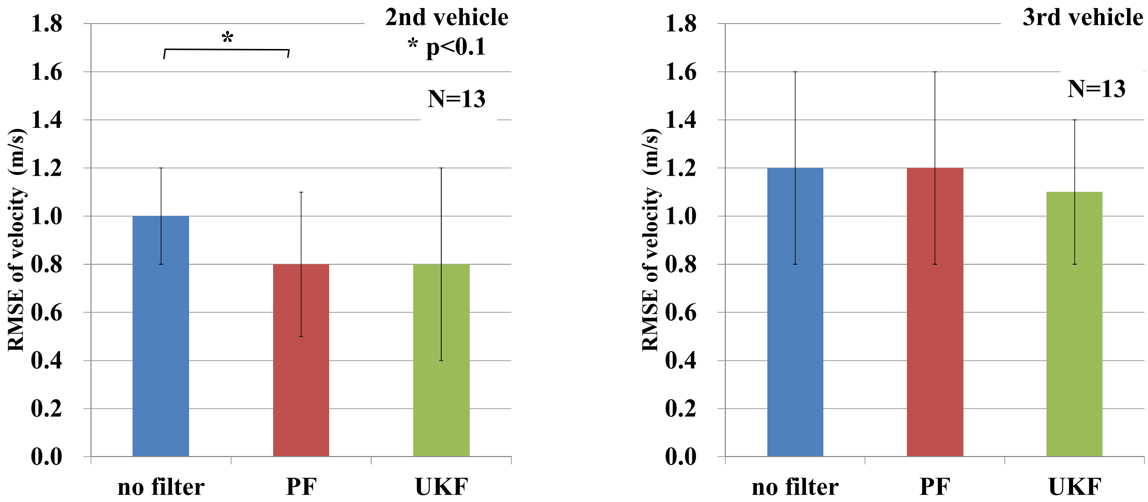

Figure 14. RMSE of velocity estimations (measuring acceleration only)

5.3 Estimation Results by Measuring both Acceleration and Velocity

An example of the Estimates by PF and UKF when measuring both acceleration and velocity are depicted in Figures 15 and 16 for the same scenario RS4. Although the PF and UKF still yield the outputs that are very close to the target, the precision is slightly worse compared to the case when observing acceleration only. In total, however, there is no difference in the mean estimation errors between the cases with and without the velocity observation, as depicted in Figures 17 and 18.

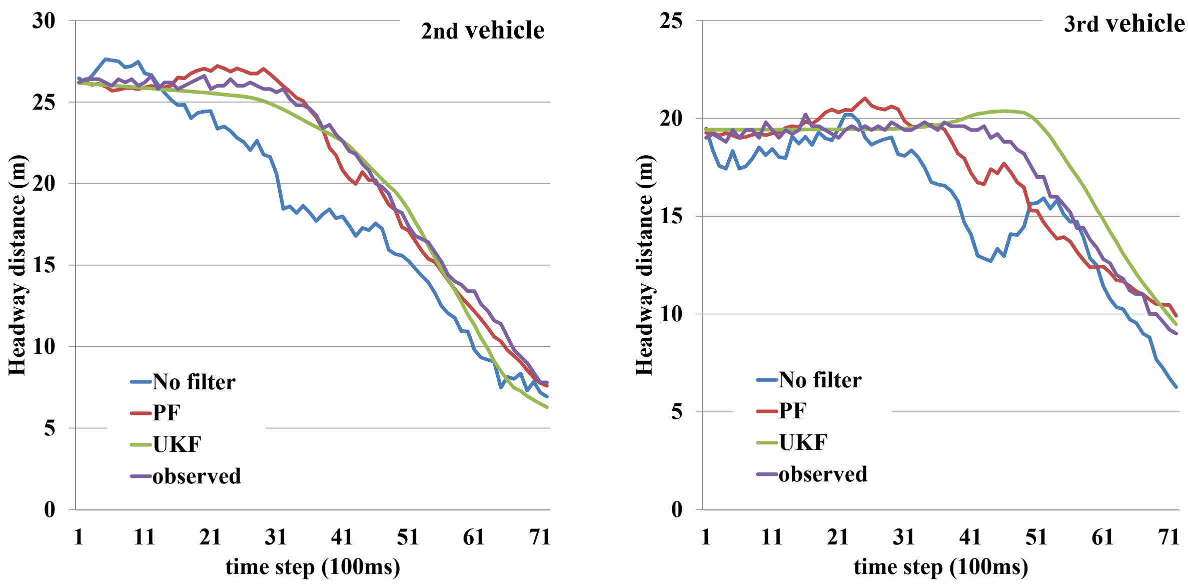

Figure 15. Estimates of headway distance in scenario RS4 (measuring acceleration and velocity)

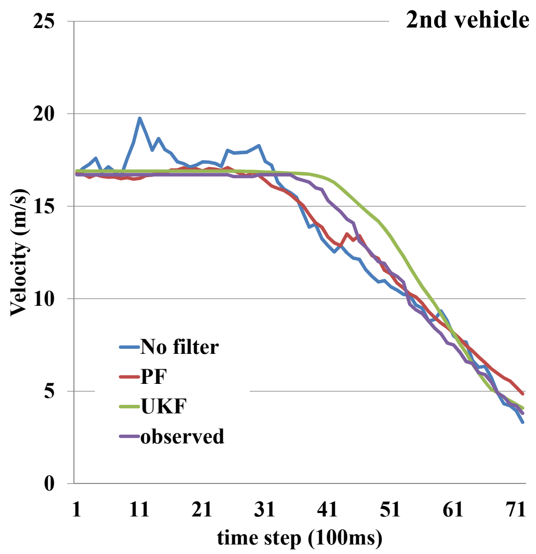

Figure 16. Estimates of velocity in scenario RS4 (measuring acceleration and velocity)

As illustrated in Figures 17 and 18, however, the mean errors by PF and UKF still remain small at the satisfactorily levels for both headway and velocity estimations. Although there has been a variation in estimation accuracy depending on the car-following data or the measurement variables, acceleration and/or velocity at the 3rd vehicle are enough to estimate the headway which is difficult to be directly measured.

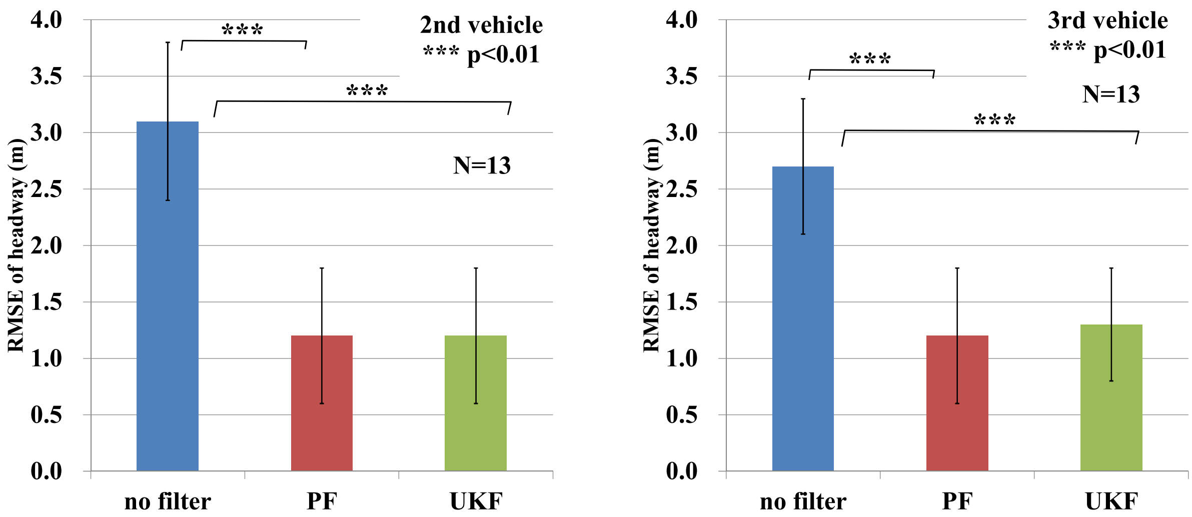

Figure 17. RMSE of headway distance estimations (measuring acceleration and velocity)

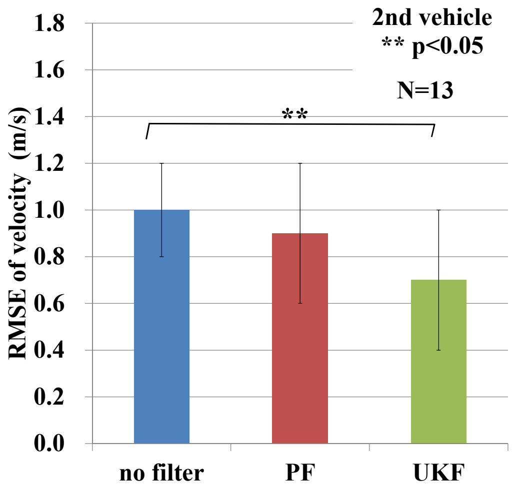

Figure 18. RMSE of velocity estimations (measuring acceleration and velocity)

Concluding Remarks

This research applied both the PF and the UKF to the state estimation of vehicle platooning, instead of conventional approaches such as the EKF or the NKF. Headway distance and the velocity of a three-vehicle platoon were estimated by observing the acceleration rate and/or velocity of the third vehicle as a probe car. The particles or sigma points generated through the PF and UKF are expected to capture the posterior mean and covariance of the true state variables to yield a more accurate estimate than the EKF and NKF.

Numerical analyses using artificial car-following data demonstrated that the PF and NKF provided significantly and statistically higher accuracy of the estimates compared to the other estimators in both the case where only acceleration is observed and that where velocity is also measured. Not only is the error small, but also the error variance is small, so that the PF and UKF yield stable and accurate estimates in all the examined car-following cases. Even in the evaluation using real car-following data collected through a test track field test, the estimation accuracy is as low as a satisfactorily level although the estimation error is slightly larger than the case using the artificial data.

Even without equipping vehicles with costly sensors or cameras to measure the headway distance, the proposed algorithm is expected to approximate headway distance in real time. However, the significant performance of PF and UKF demonstrated here is solely limited only for the three-vehicle platoon and short time car-following. Further work should be carried out to apply the estimation to a larger platoon system and the much longer period of car-following including various acceleration and deceleration situations.

Acknowledgment

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