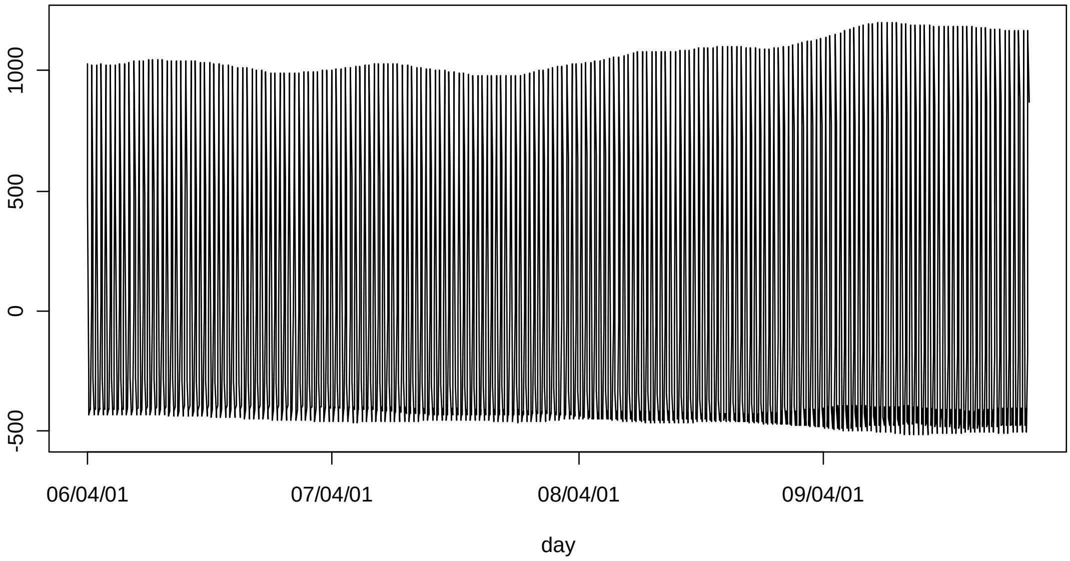

Figure-2 The series of cyclical (the day of week) effect

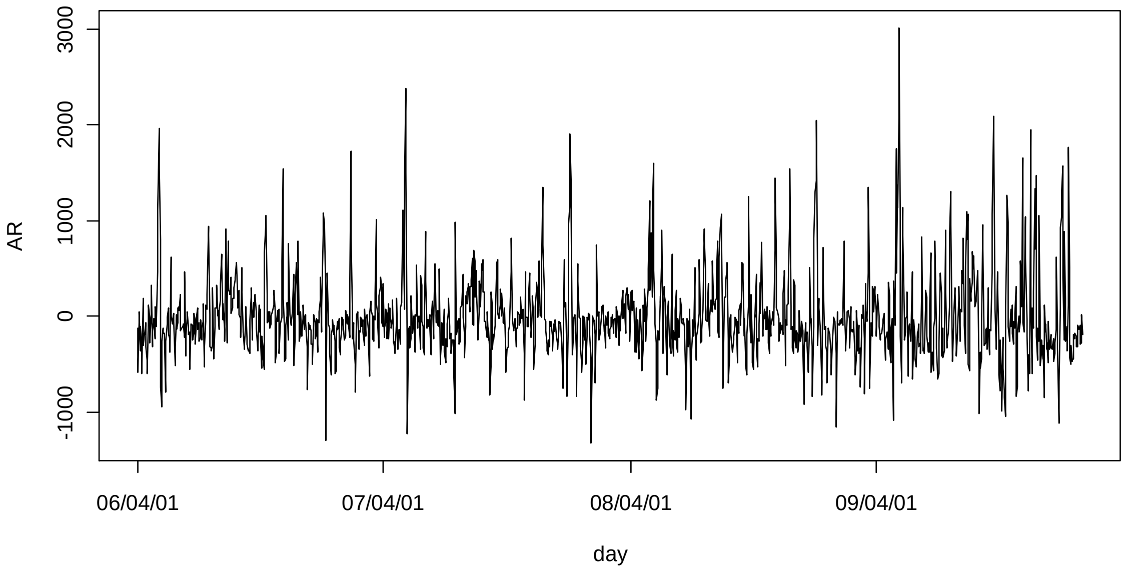

Figure-3 The series of autoregressive factor

The proposed model that uses the Kalman filter algorithm can interpolate when some measured data is missing and can extrapolate the prediction when long term prediction is necessary. For example, the Figure-5 indicates the prediction of the traffic volume from January to February 2008 that is extrapolated by the data till December 2007, while Figure-4 shows the prediction of the traffic volume in February 2008 by extrapolating by the data till January 2008. The model reduces the error in the prediction about the traffic- volume in February by adding one-month date. These Figures show the estimated state after the smoothing process. The estimated state after smoothing is mostly consistent with the actual traffic volume.

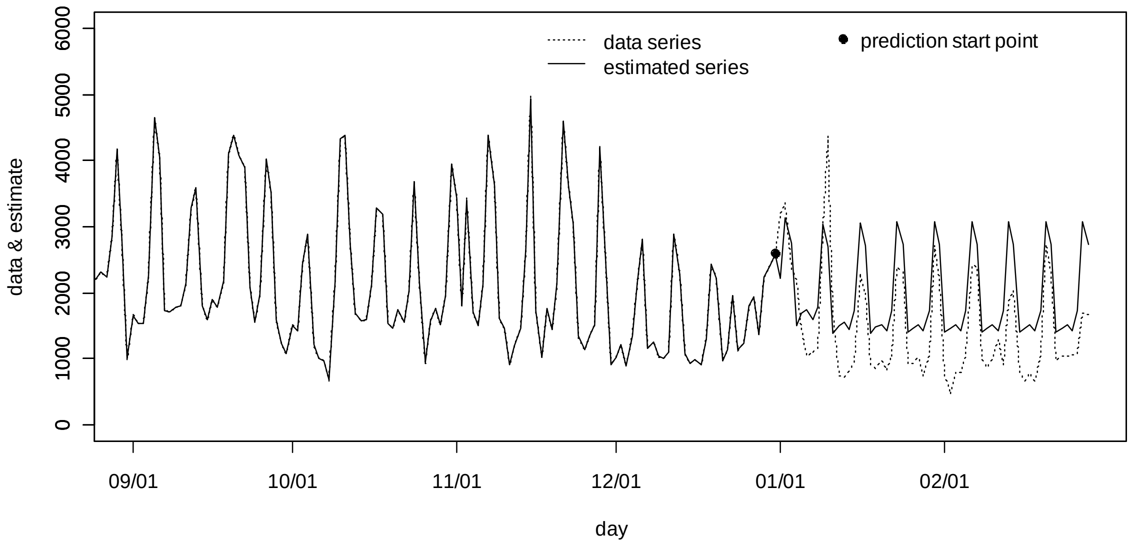

Figure-4 Extrapolating traffic volume with the data till 12/31/2008

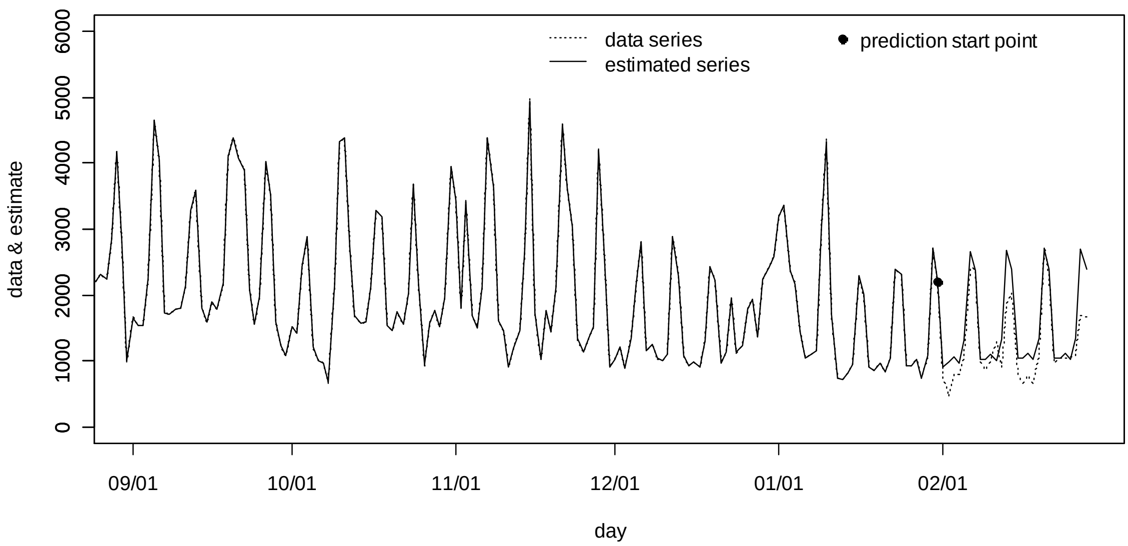

Figure-5 Extrapolating traffic volume with the data till 01/31/2009

One of the parameters estimated in this model is the variance of the error term of measurement equation. This variance can be figured out by the data on each time point. Therefore, we calculated it and showed it in the Figure-6. Though the variance is large at the initial stage, it is stable after about a couple of month. That is, the minimum period of data we need to get more precise result is about 60 days to 90 days. The more the data is used to estimate, the smaller the variance became. However, the variance increased discontinuously after 『t(March 2009)t』 again. This increase suggests that the demand structure of this expressway itself has changed so that we cannot expect no change when we apply the same model to the post-change situation. Nonetheless, we can expect this increased variance to be readjusted in this model in a few weeks by this graph.

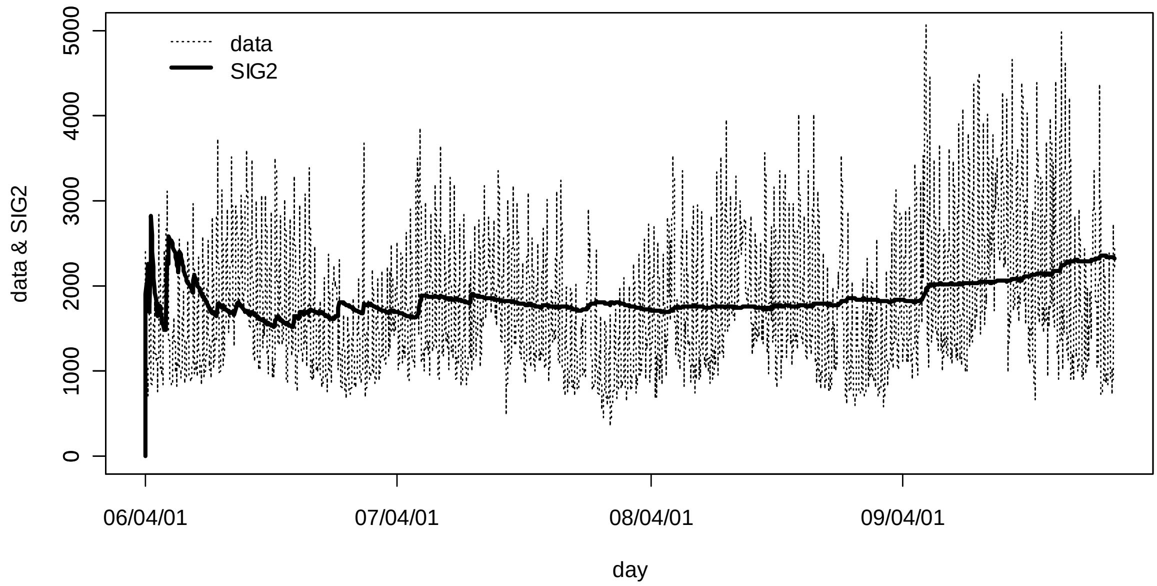

Figure-6 The expectation of measurement error estimated by the data until each time point

4. SUMMARY

This study applied the state-space model with the Kalman filter to the day traffic volume of the expressway. Two purpose mainly motivated us to apply this type of model. One is to detect the change in the demand structure of expressway caused by the drastic change of the toll charge. Because the common statistical models assume a stable demand structure, no structural change can be detected automatically. Another purpose is to develop a model that can apply the updating data to the prediction of the traffic demand. Though the recent progress in the measurement system allows us to use the updating data, the data size becomes too big to analyze using the limited calculation resources. That is why we applied the recurrent equation model to reduce the calculation load. The model identified three factors as the sources of the variation of traffic volume, the trend, the week-day factor and the autoregressive factor. We found these three factors changed significantly after the toll charge in 2009 in Japan. After the toll change, the difference of the traffic volume between weekday and weekend increased and the trend of the traffic volume turned into increasing, while the variance of the auto-regressive factor increased.

The advantage of this study is that it uses only the daily traffic volume as the necessary data. Also, the effect of these factors can be measured as numeric change. Since this approach is less load of computation and finds the structural change automatically, it will become more important in the ITS era which yields massive and purposeless data. This study has assumed a linear structure of the state transition for simplicity on one expressway traffic volume. In applying this model to the network traffic, we need to introduce more complicated state transition system because of the complex characteristics of traffic. Nevertheless, we do conclude that this study showed the first step of updating method of the travel demand prediction by using the traffic volume.

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