Journal of the Korean Society of Surveying, Geodesy, Photogrammetry and Cartography
Vol. 33, No. 6, 569-577, 2015
http://dx.doi.org/10.7848/ksgpc.2015.33.6.569

ISSN 1598-4850(Print)
ISSN 2288-260X(Online)
Original article

The Evaluation of the Various Update Conditions on the Performance of Gravity Gradient Referenced Navigation

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Abstract

The navigation algorithm developed based on the extended Kalman filter (EKF) sometimes diverges when the linearity between the measurements and the states is not preserved. In this study, new update conditions together with two conditions from previous study for gravity gradient referenced navigation (GGRN) were deduced for the filter performance. Also, the effect of each update conditions was evaluated imposing the various magnitudes of the database (DB) and the sensor errors. In case the DB and the sensor errors were supposed to 0.1 Eo and 0.01 Eo, the navigation performance was improved in the eight trajectories by using part of gravity gradient components that independently estimate states located within trust boundary. When applying only the components showing larger variation, around 200% of improvement was found. Even the DB and sensor error were supposed to 3 Eo, six update conditions improved performance in at least seven trajectories. More than five trajectories generated better results with 5 Eo error of the DB and the sensor. Especially, two update conditions successfully control divergence, and bounded the navigation error to the 1/10 level. However, these update conditions could not be generalized for all trajectories so that it is recommended to apply update conditions at the stage of planning, or as an index of precision of GGRN when combine with various types of geophysical data and algorithm.

Keywords : GGRN, EKF, Update Conditions, Stabilization of the Filter

1. Introduction

As an alternative navigation system for the non-global navigation satellite system (GNSS) environment, the database referenced navigation (DBRN), which uses various geophysical information such as terrain, gravity and magnetic data, is being studied. Especially, many studies have expressed particular interest in the gravity gradient referenced navigation (GGRN) as the future technique. According to the development of the small and precise gradiometer, some feasibility analyses assuming the precise sensor to be developed in the future have been reported (DeGregoria, 2010; Liu *et al*., 2010; Richeson, 2008; Rogers, 2009). Lee and Kwon (2014) constructed the six gravity gradient DBs based on terrain and gravity data over the entire Korean peninsula, and analyzed the effect of various factors (e.g., DB/sensor error, flight altitude, initial errors, DB resolution, and update interval) on the navigation performance. Also, two specific update conditions that determine the update time and select some reliable components are tested. In the aforementioned study, however, only four and five trajectories for each condition showed improvement on the performance in total of fourteen trajectories.

Received 2015. 12. 01, Revised 2015. 12. 14, Accepted 2015. 12. 18
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In this study, new update conditions are proposed considering the consistency of the correction direction and magnitude. In the performance analysis stage, various DB and sensor errors were applied to check if those update conditions improve the performance of the GGRN, despite the relatively low precision of the DB and the sensor.

2. Update Conditions

The general algorithm for the DBRN is a sequential processing: this algorithm uses a variety of filters (e.g., extended Kalman filter (EKF), unscented Kalman filter (UKF), bank of Kalman filter (BKF), and point mass filter (PMF)). Among the various filters, the EKF is the most broadly applied due to the relatively low complexity and faster convergence time. Its main disadvantage is that it provides precise results when only the linearity between the measurements and the states is preserved. If the wrong correction is applied to the solution, the filter could diverge. Therefore, filter stabilization methods are necessary to determine the specific updated time, or select reliable measurements among the gravity gradient DBs. Lee and Kwon (2014) suggested a couple of update conditions that use the relation between the DB/sensor error and filter measurements, and the roughness of the gravity gradient DBs. However, the number of trajectories with improved navigation results has remained about 30% level. The primary purpose of this study is to suggest new update conditions to stabilize the GGRN algorithm. The principal direction to find the update conditions has been maintained to be two groups; the first group determines the specific update time, and the second group selects some of the gravity gradient components. To link up with the preliminary study, each group includes the previous update condition from the Lee and Kwon (2014) as the first condition; and one and four new update conditions have been appended to the Group 1 and 2, respectively.

2.1 Group 1: Determination of specific update time

To assure precise navigation results, it is important to find a proper update time when the measurements and the states meet the condition of linearity. Once the wrong correction occurs, a filter could diverge or a navigation error could increase until the proper correction is applied to compensate the inertial navigation system (INS) error. In this case, it would be better to fly with a pure-INS, rather than use a fixed update interval (e.g., 1, 10 or 20 seconds). In this study, two update conditions have been suggested to find specific update time considering the relation between the DB/sensor error and the filter measurements as well as the consistency of the direction of the estimated states.

- **Update Condition 1: Relation between DB/sensor error and filter measurements**

In GGRN, filter measurements are composed of the difference between the gravity gradiometer measurements and the extracted gravity gradient from DBs. If it is smaller than the DB/sensor error, it is difficult to judge whether it is the actual difference or it came from the measurement and DB errors. Therefore, the filter compensates INS error using full tensor when any filter measurements are larger than the sum of the DB and the sensor error. For furthermore understanding on the detailed concept, please refer to Lee and Kwon (2014).

- **Update Condition 2: Consistency of direction of estimated states**

If it is assumed that the GGRN uses a full tensor gradiometer (FTG) type gradiometer, six gravity gradients would be applied to the navigation. In the previous study, a filter was designed to use those components as a set of measurements. Because each gravity gradient has different characteristics for the target area, it is possible to compose them as an independent filter like terrain referenced navigation (TRN). In that case, the six sets of estimated states ($\bar{x}_{k,comp}$, $comp=NN,NE,ND,EE,ED,DD$) showing different magnitude and direction of the correction would be generated. It is clear that the direction of the correction should be consistent if the linearity between the measurements and the states are preserved. Therefore, the filter could be set to compensate the INS error when the estimated states indicate one-sided direction. To find the absolute update time, whether both latitude and longitude illustrate one-leading direction or not has been checked. This is because the possibility that shows a single direction for both latitude and longitude is relatively small. When this condition is satisfied, all six components are applied to estimate the final correction.

2.2 Group 2: Selection of reliable gravity gradient components

To find out the effect of the number of gravity gradient components on the navigation performance, simulation tests were conducted based on the two trajectories generated in the low and high variation region (latitude 35~35.5°, longitude 127° and 128.5°). As a result, two combinations generated better navigation results, although only four or five components were applied as filter measurements. This means that it is appropriate to select some reliable components to improve the navigation results. Therefore, new update conditions that select and use part of the gravity gradient components were deduced by considering the standard deviation of the DB, the residuals, the direction and the magnitude of the states.

- Update Condition 3: Standard deviation of the DB

Previous studies addressed that better navigation results appear with the geophysical DB representing huge variation in the target area (Li *et al*., 1996; Titterton and John, 2004). For example, the profile matching algorithm stacks the measured terrain information for several seconds and compares it to the DB; then it updates the position when the standard deviation of the generated profile is large. Similarly, the standard deviation of the gravity gradient DBs were calculated at the update time, and DBs with a value larger than 10% of the standard deviation from the entire area were selected in the previous study (Lee and Kwon, 2014). To guarantee stable navigation results, the filter compensated the INS error when the total number of selected DBs was larger than two.

- Update Condition 4 and 5: Residuals

As mentioned previously, the key to generating stable navigation results in the EKF is the linearity between the measurements and the states. When this condition is satisfied, the difference between the measurements (z_k) and the estimated measurements ($\hat{z}_k$) calculated by applying the estimated states ($\bar{x}_k$), is very small. This difference is called the residual (Eq. (1)).

$$v_k = z_k - \hat{z}_k, \quad \hat{z}_k = H_k \bar{x}_k \tag{1}$$

where v_k is residual vector, z_k is the measurement vector composed of the difference between the gravity gradiometer measurements and the extracted gravity gradient from DBs, $\hat{z}_k$ is the estimated measurements vector calculated by applying estimated states $\bar{x}_k$, and H_k is design matrix.

In the case of GGRN, six components could be applied as a set of measurements, or each component could be applied independently. It means that two types of estimated states (i.e., $\bar{x}_{k,full}$ from full tensor, $\bar{x}_{k,comp}$ from each gravity gradient DB) could be calculated by the filter. Therefore, two types of residuals (i.e., $v_{k,full}$ and $v_{k,comp}$) are derived by applying $\bar{x}_{k,full}$ and $\bar{x}_{k,comp}$, respectively. Only the part of the components showing residual smaller than the sum of the DB and sensor error was selected for the INS error compensation. Update Condition 4 is the case that applies $v_{k,full}$ and Update Condition 5 uses $v_{k,comp}$.

- Update Condition 6. Consistency of direction of estimated states

This is a modified version of the Update Condition 2 in Group 1. In the previous section, the direction of the estimated states was checked to determine the proper update time. If it is assumed that this kind of one-sided direction of correction has a large possibility for an appropriate correction, it would be appropriate to use some of the components indicating a single direction. To extract the reliable components, the common components were selected and applied for the navigation error compensation.

- Update Condition 7. Statistics of estimated states

The mean ($\bar{y}$) is the statistically expected value of the unknown, and the standard deviation (S) limits the region of certainty around the mean. Therefore, it is possible to extract reliable components by applying the mean and standard deviation to limit the trust region. In this study, the trust region has been restricted to the $\bar{y} \pm 2S$; the part of the components located within this region were applied for the INS error compensation. The estimated components are calculated from each gravity gradient.

In sum, Update Condition 1 and 2 assume that an intermittent update could allow more stable navigation results so that filter compensates the INS error by using full tensor when the update conditions are satisfied. Update Condition 3 to 7 suggest a way to find the reliable components, because they assume that the navigation results would be improved by applying only some of the components. Please note that Update Condition 1 and 3 were derived from the previous study.

3. Simulation Results

The effect of the update conditions on the navigation performance has been evaluated based on the simulation. In the simulation, it was assumed that the aircraft flies with a navigation-grade inertial measurement unit (IMU; model: LN100), six gravity gradient DBs and a FTG gradiometer. In addition, the barometric altimeter and compass were loaded as alternative sensors to compensate the height and the yaw errors of INS. The flight altitude and speed are 3,000 m and 350 km/h, respectively. Please refer to Lee and Kwon (2014) to find out the detailed sensor specifications and the distribution of the trajectories. The navigation performance according to the update conditions was evaluated by comparing it to the case obtained without update condition.

Table 1 shows the horizontal position error for the entire trajectories when the DB and the sensor error were supposed to be 0.1 Eo and 0.01 Eo. To evaluate the effect of each update conditions on the performance, both the navigation results from the pure GGRN that does not use any update conditions and the TRN are also listed. The performance ratio with respect to the results obtained without update conditions is shown in Table 2. Based on the simulation results, it was found that four and eight trajectories showed improved navigation performance with Update Condition 1 and 2, respectively. For the other five update conditions that belong to Group 2, it was found that the number of trajectories generated better navigation results are five, seven, eight, six, and seven, respectively.

In the previous study, GGRN showed less precise results at trajectory no. 5, 8, 13, and 14 compared to the results from TRN when no update conditions were applied. To make it clear, the trajectories showed poorer navigation results than the TRN are marked with '*' in the Table 1. It is found that

Table 1. Horizontal position error for entire trajectories (unit: m; * shows poor navigation results on GGRN than TRN)

Traj. no.	Full Tensor without Update Condition	Update Condition							TRN
		1	2	3	4	5	6	7	
1	6.509	9.081	7.356	9.562	6.871	6.946	6.912	6.525	12.43
2	5.747	6.207	6.008	6.480	6.403	6.521	7.093	5.939	5.95
3	5.744	6.212	5.362	6.389	5.663	5.659	5.673	5.541	7.94
4	5.040	4.234	5.480	4.789	6.916	7.172	7.311	4.911	6.20
5	11.681	14.883	12.548	5.877	15.803	15.950	16.988	11.912	4.08*
6	4.475	4.869	5.140	5.853	5.222	5.269	9.245	4.494	5.93
7	11.920	10.582	9.898	5.927	11.197	11.204	11.591	10.960	16.63
8	8.673	8.112	8.367	10.560	7.845	7.855	9.226	9.313	8.60*
9	10.798	14.414	10.092	7.577	7.923	7.599	10.522	9.548	20.28
10	15.278	16.641	19.250	11.362	18.683	18.625	18.886	18.127	22.59
11	12.431	13.517	12.060	97.297	11.946	11.881	11.310	12.927	13.90
12	4.076	4.684	4.009	4.386	4.005	3.958	5.562	3.961	15.38
13	6.835	9.303	5.518	11.271	5.374	5.517	6.693	6.709	5.82*
14	8.948	8.547	8.745	12.314	9.018	8.295	7.877	8.558	4.39*

Table 2. The performance ratio with respect to the no update conditions (%) and the number of trajectories that generate better results

Traj. no.	Update Condition						
	1	2	3	4	5	6	7
1	71.675	88.476	68.072	94.728	93.700	94.164	99.754
2	92.578	95.650	88.682	89.743	88.119	81.018	96.760
3	92.456	107.117	89.901	101.424	101.497	101.250	103.661
4	119.035	91.957	105.233	72.868	70.270	68.928	102.618
5	78.484	93.084	198.736	73.914	73.231	68.758	98.060
6	91.918	87.069	76.467	85.701	84.937	48.405	99.588
7	112.649	120.434	201.112	106.459	106.393	102.841	108.758
8	106.914	103.659	82.135	110.558	110.417	94.014	93.132
9	74.914	106.994	142.505	136.296	142.104	102.629	113.097
10	91.812	79.366	134.471	81.773	82.029	80.896	84.284
11	91.964	103.074	12.776	104.062	104.631	109.914	96.163
12	87.024	101.687	92.939	101.775	102.986	73.292	102.913
13	73.475	123.876	60.646	127.182	123.899	102.130	101.886
14	104.694	102.318	72.662	99.222	107.875	113.588	104.556
*	4	8	5	7	8	6	7

* indicates the number of trajectories showing improvement due to update conditions

huge improvement on the navigation performance appeared when update conditions were used. For example, trajectory no. 8 showed more stable results than the TRN, when Update Condition 1, 2, 4, and 5 were applied. In addition, the horizontal error decreased in trajectory no. 13 when Update Condition 2, 4, and 5 were used. However, trajectory no. 5 and 14 yielded poorer results than the TRN.

Because each trajectory shows different local characteristics, the effect of the update conditions is not consistent. Some trajectories show better navigation results with the update conditions, but some does not. For example, the GGRN performance has been improved at trajectory no. 7 regardless of any update conditions. However, trajectory no. 5 and 10 that fly above relatively smooth regions generated more precise results when only the Update Condition 3 was applied. In the case of trajectory no. 1, 2 and 6, any update conditions did not improve the navigation performance.

Therefore, two trajectories were selected to find out the effect of the update conditions more closely. Trajectory no. 7 was selected as a representative showing positive impact with the update condition. Trajectory no. 6 was selected as a control group, because it did not show any improvement with any update condition. In addition, the performance ratio at trajectory no. 6 remained less than 50% by applying the Update Condition 6.

Fig. 1 shows the horizontal position error and gravity gradient variation in trajectory no. 7. Since the update conditions were grouped into 2 groups, horizontal position errors were plotted separately. Trajectory no. 7 starts from latitude 35° to 38° and the longitude is 128.5°. As shown in the Fig. 1, the gravity gradient variation is very small for the first few hundred seconds. In this kind of situation, the extracted gravity gradients from the DB do not vary much within few km boundaries, so that the filter measurements is difficult to be assured if it is a real gravity signal. Also, a large residual or inconsistency in the correction direction appears frequently. Obviously, the effect of the update conditions well appeared in this case showing smaller horizontal error. In the case of Update Condition 1, the navigation performance has been improved about 113%. During the entire flight, 1,147 times of updates that is about 33% of the total update time were applied. It means that it would be possible to guarantee stable navigation results with the intermittent update. When Update Condition 2 was applied, 120% of an improvement appeared with 1,199 times of updates. Among the total of 3,430 updates, Update Condition 4 and 5 compensated the INS error 2,287 and 2,286 times with a full tensor. Update Condition 6 used part of the components 1,847 times; the number of times that used five components was 268. Although these update conditions did not apply the full tensor for the navigation, navigation results were improved. A huge improvement appeared when the Update Condition 3 was applied. Because Update Condition 3 compensates the INS error when the local standard deviation is large, GGRN had to fly with a pure INS for about 150 seconds. As a result, it prohibited the wrong correction, so that the performance has been improved up to 200% level.

On the other hand, trajectory no. 6 showed less precise results when the update conditions were applied. As shown in Fig. 2, no update condition bounds the horizontal position error; it also resulted in unstable navigation results. Especially, relatively large horizontal error appeared over the entire flight with Update Condition 6, such that the performance ratio with respect to the results without update condition remained at less than 50% level.

When comparing trajectory no. 6 and 7, a large difference existed in the local gravity gradient variation. In the case of DBRN, more precise navigation results would be obtained when the geophysical data show a large variation. However, the problem is that the possibility of a wrong correction would increase if the geophysical data abruptly changes. It means that the filter would compensate the horizontal position error to the wrong direction because the true and INS indicated positions could be located at the different slopes. Similarly, GGRN sometimes meets this kind of situation when the gravity gradient DBs do not have consistent characteristics. If so, selecting some components would compensate the INS error in the wrong direction with a larger error. Therefore, it would be better to use the full tensor because six components could compensate each other. The performance also decreases dramatically once the wrong correction occurs. As such, it is necessary to compensate frequently, instead of applying an intermittent update, to force the filter to converge as soon as possible. As a consequence, better navigation results appear when the filter updated every epoch with the full tensor in trajectory no. 6.

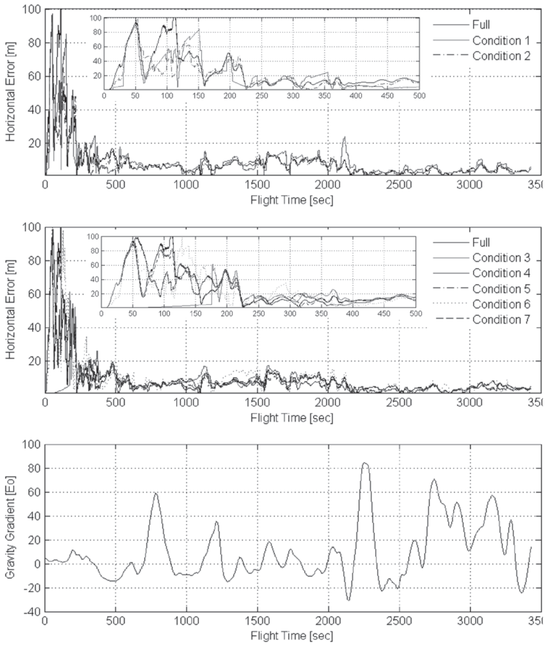

Fig. 1. Horizontal error according to the update conditions and gravity gradient variation in trajectory no. 7

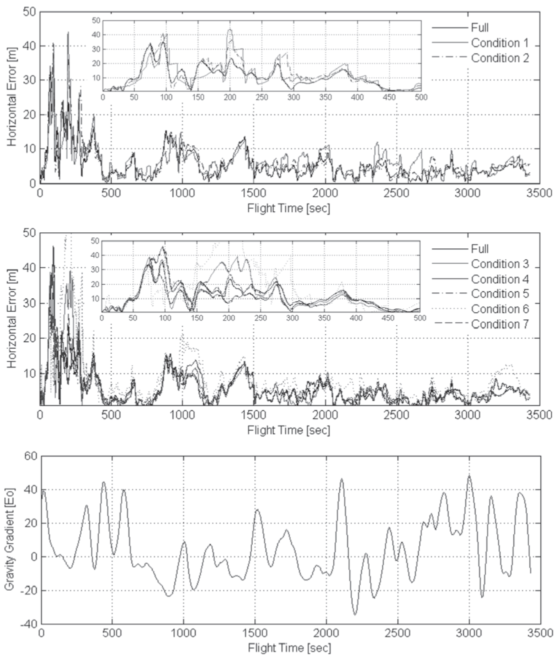

Fig. 2. Horizontal error according to the update conditions and gravity gradient variation in trajectory no. 6

In the analysis of the GGRN performance based on the simulation, it was emphasized that 0.1 Eo and 0.01 Eo level of the precise gravity gradient DB and sensor should be applied for the navigation when the flight altitude is higher than 2000 m. If less precise DB and sensor are assumed, GGRN would not result in a similar or better navigation performance compared to the TRN. Because the main purpose of this investing was to deduce such update conditions for the stabilization and improvement of the GGRN, additional simulation tests were performed assuming a lower grade DB and sensor to check whether the update conditions compensate the INS error efficiently. The pair of the DB and the sensor errors were assumed to be 1 - 0.1, 3 - 3, and 5 - 5 Eo. The navigation performance was evaluated by comparing the results from the no update condition applied. Table 3 shows the number of trajectories that generate better navigation results when update conditions were applied.

Table 3. The number of trajectories showing better navigation results with respect to the no update condition applied case

DB-Sensor Error [Eo]	Update Condition						
	1	2	3	4	5	6	7
1 – 0.1	3	7	6	7	7	4	11
3 - 3	7	8	5	8	9	8	9
5 - 5	7	6	6	6	7	5	9

When the DB and the sensors error were supposed to the 1 Eo and 0.1Eo, Update Condition 1 and 6 were found to better navigation results only in the three and four trajectories. However, Update Condition 2, 4 and 5 showed improved performance in the seven trajectories at the 50% level. Update Condition 7 was evaluated as the most effective update condition, because a total of eleven trajectories equivalent to 78% were improved by applying this condition. As illustrated in Fig. 3, most trajectories showed better navigation. Although three trajectories generated less precise results, the navigation performance of two trajectories was about 99% and 98% levels. In the other words, it is not a significant degradation of the performance.

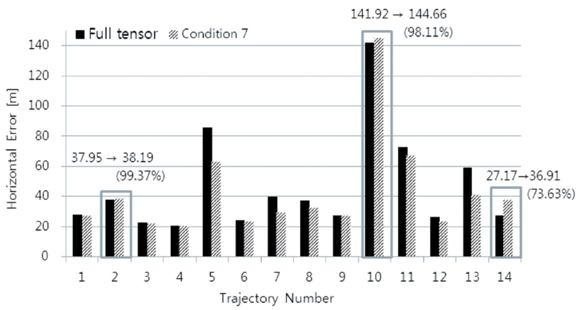

Fig. 3. Horizontal position error without update condition and with update condition(DB - Sensor error : 1 - 0.1 Eo)

In case the DB and the sensor errors were supposed to be 3 Eo or 5 Eo, that are the precision of the commercial sensor, each condition generated relatively fair improvements. As found in Table 3, there was a large difference in the number of trajectories showing better performance according to the update conditions when the DB and the sensor have 1 Eo and 0.1 Eo precision. When the DB and sensor error were assumed as 3 Eo, each update condition (except Update Condition 3) generated better navigation results in at least seven trajectories. Although Update Condition 5 and 7 generated better navigation results in two more trajectories, the difference in the number of trajectories that shows an improvement is not that significant. Also, it was found that each update condition derived performance improvements more than five trajectories with 5 Eo of the DB and the sensor errors, respectively.

The effect of the update conditions on the navigation performance was more powerful when the aircraft flies with a lower precision of DBs and gradiometer. For example, trajectory no. 10 diverged when both DB and sensor errors were 5 Eo, despite the compensation of INS error with full tensor every epoch. However, the horizontal error decreased with Update Condition 2, 4, 5, 6 and 7. Especially, Update Condition 2 and 7 bound the navigation error to the 1/10 level. To check the effect of the update conditions, the navigation results in trajectory no. 10 were plotted in Fig. 4.

For reference, a total 2,286 times of updates are necessary when the filter compensates the INS error every epoch. However, 1,633 times of updates, that is about 71.4% of the total updates, were applied when Update

Condition 2 was applied, and the horizontal position error was bounded less than 50m. When the INS error was compensated by using Update Condition 4 and 5, the navigation performance was improved more than twice with 970 times and 1,012 times of updates that are 42% and 44% of full updates. In the case of Update Condition 6, it was found that the 80m level of horizontal navigation precision was obtained with 1,576 times of update. Among 1,526 update times, the ratio that used the full tensor was 5.6%, about 73% used less than four components for the INS error compensation. Update Condition 7, that uses part of components locate within the 2 standard deviation region, showed about 50m of horizontal position error. Among entire updates, most states were estimated using a full tensor, only 6% used five components. Although the ratio that uses part of the components is not that large, it was found that the horizontal precision has been improved about 10 times. However, Update Condition 1 degraded the performance, so that the horizontal position only remained at the 30% level compared to the results obtained by compensating with a full tensor every epoch.

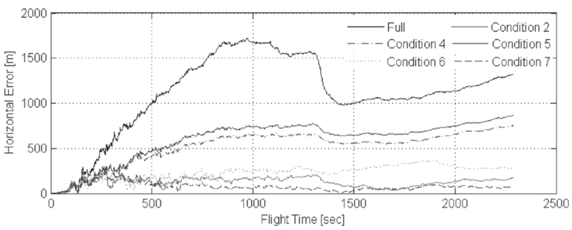

Fig. 4. Horizontal error according to the update conditions in trajectory no. 10

It should be mentioned that it is difficult to generalize these update conditions for all trajectories. However, a few hundred meters of horizontal errors have been bounded to the few tens of meters when update conditions make a positive effect on the navigation results. In addition, Update Condition 7 improved the performance in more than nine trajectories regardless of the DB and sensor error. It means that the suggested update conditions are the meaningful once they work properly. Therefore, more stable navigation results would be obtained by applying these update conditions in the planning stage.

4. Conclusion

To construct a more stable and reliable GGRN algorithm, a total of seven update conditions that find the proper update time or some reliable components were derived, and the effect of each update condition on the navigation performance was evaluated.

When the DB and sensor errors were supposed to 0.1 Eo and 0.01 Eo, more precise navigation results in the more than half of the trajectories appeared when find update time or select part of components by checking the consistency of the direction of independently estimated states to the latitude and longitude direction. When comparing two trajectories that showed improvement and degradation according to the update conditions, it was found that it would be better not to use update condition if the gravity gradient components show relatively huge variation. Therefore, the analysis of gravity gradient change in the target area should be performed to find proper update condition as well as make the positive effect on the navigation performance.

Even a larger DB and sensors were applied, the improved navigation results were derived from many trajectories. Update Condition 7, which selected part of components that independently estimated states locate within trust boundary, generated better performance in eleven trajectories when DB and sensor error were 1 Eo and 0.1 Eo. In case the DB and the sensor errors were supposed to 3 Eo, most update conditions derived improvements in at least seven trajectories. In addition, it was found that more than five trajectories showed better navigation results despite 5 Eo error of the DB and the sensor error, if update conditions were applied. Especially, a few hundred meters of horizontal errors decreased to a few tens of meters by applying the update condition in trajectory no. 10. However, it should be mentioned that those update conditions could not be generalized. Therefore, these update conditions should be properly applied on the stage of the flight planning for more stable navigation performance. In addition, these update conditions would be applied to check the reliability of the GGRN to develop combined navigation system that uses multi-geophysical data and algorithms.

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