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Geodetic datum transformation to the global geocentric datum for seas and islands around Korea

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ABSTRACT: According to revisions of survey law taking effect on January 1, 2003, the Korean geodetic datum has been changed from a local geodetic to a world geodetic system. Since the datum change demands a geographical data transformation, the National Geographic Information Institute has established step-by-step plans for the transformation of the land data constructed through the National GIS Project, and it is in progress. For maritime data, however, no detailed transformation plan has been established yet. Therefore, it is necessary to analyze the maritime geographic data obtained through the Maritime GIS project and set up the data transformation scheme to a world geodetic system. In this study, the datum transformation parameters especially for the maritime geographical data are determined. From database constructed through MGIS, a total of 492 coordinate pairs were used in parameter determination initially. At this stage, three popular seven parameter transformation models, Bursa-Wolf, Molodensky and Veis model, and the multi regression equation are applied, and the transformation parameters from the Molodensky model are selected for its accuracy and consistency with the land data transformation method. To eliminate the local bias caused by the nonequally distributed stations, a network optimization is applied and 42 stations are selected to determine the final transformation parameters. The distortion after applying the similarity transformation is modeled through a least squares collocation with Gaussian model, and high accuracy better than 15 cm in coordinate transformation is obtained.

Key words: Datum Transformation, network optimization, least square collocation

1. INTRODUCTION

The fast development of information technology (IT) especially in the field of modern computer and communication links provides a huge amount of data storage, fast processing, quality visualization, and near-real-time data transfer through various networks. The impact of this information revolution accelerates the development in various scientific and engineering fields among which the field of geomatics/geoinfomatics dealing with spatial information makes the most benefits from the high computational power and generates significantly improved products in terms of data processing, analysis and visualization.

Spatial data is connected to the geographical or spatial location which is expressed by coordinates based on a coordinate system so that it can be analyzed with connection to the locations for various applications. The basis of the coordinate system is called a geodetic datum which defines the size and shape of the earth, and the origin and orientation of the coordinate systems used to map the earth. Historically, hundreds of datums have evolved, and different countries have used different datums for their own coordinate basis.

The advent of modern satellite technology such as Global Positioning System (GPS), Global Orbiting Navigation Satellite System (GLONASS) and Doppler Orbitography and Radiopositioning Integrated by Satellite (DORIS) made it possible to determine positions on or near the earth's surface with accuracy better than a couple of decimeters. Because of its accuracy, continuity and efficiency, satellite positioning is now a standard method in establishing networks and constructing a basis for spatial data. The datum being used in these satellite systems is the global geocentric one such as WGS84. To fully utilize the system, therefore, countries using different datums have to either make a datum transformation platform between their datum and the global geodetic datum, or change the datum to the global one to fully utilize the system. For this reason and growing cooperation for using the international based data set, some countries like Australia changed the national datum to the geocentric datum GDA 94 (Collier and Steed, 2001).

To keep pace with international trends and to establish the spatial data infrastructure which is compatible worldwide, Korean survey law has been revised to change the national datum to the World Geodetic Datum from January 1, 2003. Due to the revision, the constructed spatial data needs to be converted to data based on a new datum and this is done by constructing a transformation platform. The spatial data for land and ocean areas are governed by different organizations in Korea. The National Geographic Information Institute (NGII) under the Ministry of Construction and Transportation, and the

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National Oceanographic Research Institute (NORI) under the Ministry of Maritime Affairs and Fisheries are responsible for land and ocean spatial data, respectively.

The conversion to the new datum for land data was initiated relatively early compared to that for the ocean data throughout the project of Geodesy 2002 managed by NGII. Using 107 first order common points which have coordinates both in the old Bessel ellipsoid and the new GRS 80, the transformation parameters based on the Molodensky-Badekas algorithm are determined (Yoon, 2003). In addition, the distortion is modeled and corrected using least squares collocation; therefore, a final accuracy of the transformation better than 20 cm is achieved.

In October 2003, NORI initiated a project on the determination of the datum transformation parameters for ocean data. Since the data used in the determination of the transformation parameters for land data is mainly distributed in land, NORI decided to determine the independent transformation parameters so that all ocean GIS data can be transformed based on new parameters.

In this paper, the procedure and results of the Korean ocean datum transformation are presented. With a description of the data used in the determination of the transformation parameters, the detailed step-by-step procedures to achieve high accuracy in the transformation are described. Especially the optimization of the station distribution and distortion modeling are deeply investigated and described. The developed datum transformation tools, results and analyses conclude this paper.

2. DATA ACQUISITION

The data used in this study was acquired from 1997 to 2002 through the campaign for the determination of a Korean territorial baseline issued by NORI. As one can see in Figure 1, the majority of data is distributed on the shore or Islands. A total of 492 points were measured with GPS static methods at 30 second intervals for 24 hours, among which 12 and 18 control points located on land and shore area are included. The measured data was processed with GPSurvey from Trimble in baseline determination mode by fixing the control points.

For higher accuracy, using the results from the baseline determination, the network adjustment using TrimNet Plus was performed and chi-square test with 95% confidence interval was applied. In this procedure, the data that failed the test were considered to be outliers and removed, and the adjustment was reperformed to finalize the precise coordinates for 315 points.

It should be mentioned that the data is significantly dense in the area of the East Sea and southern Islands. This non-uniform distribution of data causes some biases in the estimated transformation parameters, which leads to the necessity of the optimized station distribution. The details on this effect and optimization procedures follow in the next section.

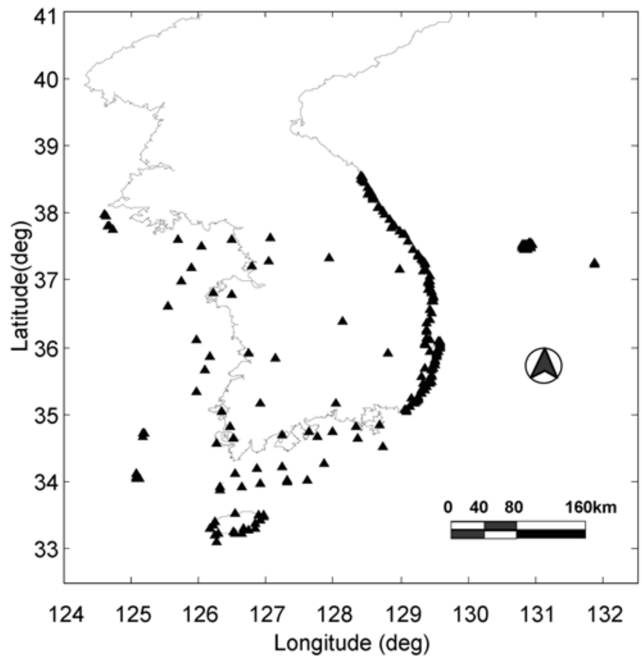

Fig. 1. Stations available for the datum transformation.

3. TRANSFORMATION PARAMETER ESTIMATION

The conditions to satisfy the national datum transformation are simplicity, efficiency, uniqueness, and rigor (Collier and Steed, 2001). In other words, one has to determine a unique transformation model which is simple to understand, fast and easy to perform, and produces best results. In geodesy, the seven-parameter similarity transformation is widely used for the datum transformation since it more or less satisfies the above conditions.

The seven-parameter similarity transformation is composed of three translations of the coordinate origin, one scale factor, and three rotation parameters. That is, coordinates from a three-dimensional Cartesian coordinate frame can be transformed into coordinates in another frame by translating the origin, applying rotation in each axis and adjusting the scale. Therefore, if coordinates from two coordinate frames are available for some common points, those transformation parameters can be estimated. In theory, three common points from two different coordinate frames are enough to estimate those seven parameters, but more common points are used in a least squares sense to eliminate the biases and achieve the high precision of the estimates.

There are some popular seven parameter similarity transformation models such as the Bursa-Wolf, Molodensky-Badekas, and Veis models. Although those models are a little bit different in the setting of the frames and concept of the transformation from one to another, the mathematical models and parameter estimation procedures are almost the same as given in the next section. For details on the transformation or above models, refer to Rapp (1993) or Harvey (1986).

Mathematically, the model for the estimation of the transformation parameters belongs to the Gauss-Helmert model, or condition equation, with parameters given as:

$$F(Y-e,\Xi) = 0 \quad (1)$$

where Y is the observation vector, e is the random error vector of normal distribution with zero mean and variance of Σ, i.e., $e \sim N(0, \Sigma)$, and Ξ is the parameter to estimate. Generally, Equation 1 is given in nonlinear form so it can be linearized by Taylor series expansion:

$$F(Y,\Xi^0)+\left.\frac{\partial F}{\partial \Xi}\right|_{\Xi=\Xi_0}\cdot\xi-\left.\frac{\partial F}{\partial Y}\right|_{Y=Y_0}.e=0 \Rightarrow w+A\xi-Be=0 \quad (2)$$

where Ξ^o is the initial value for the expansion, ξ is the difference between the parameter and the initial value.

The estimates through least squares adjustment for the above model are then given as:

$$\hat{\xi} = [A^T(B\Sigma B^T)^{-1}A]^{-1}A^T(B\Sigma B^T)^{-1}w \quad (3)$$

Using 315 stations of data described above, the transformation parameters for all three models are estimated based on Equation 3. Table 1 shows the estimated parameters with standard deviations.

As one can see in the above table, the Bursa-Wolf model has larger standard deviations of the estimates than the other two models. The main reason for this is the orientation origin of the Bursa-Wolf model. In other words, the origin of the rotation in the Bursa-Wolf model is at the mass center of the earth while the data used are only from Korea, which is significantly biased in a global sense. Therefore, the biased direction of the data caused poor estimates in the Bursa-Wolf model.

The other two models, however, use a local origin as the rotational origin, thus rotational parameters are relatively well estimated. It should be noted that the scale factors are the same in all three models and so are translations for the Molodensky-Badekas and Veis models. Thus, the difference between the Molodensky-Badekas and Veis models appears in the rotation parameters only. The reason for this would be the configuration of the coordinate systems in the models. While the Molodensky-Badekas model rotates the local xyz frame to the new frame, the Veis model rotates the local NED frame to the new frame (Rapp, 1993).

Although the superiority between the Molodensky-Badekas and Veis models was not clearly found, the Molodensky-Badekas model is selected as the datum transformation model for Korean ocean spatial data. The rationales for this decision are the selection of the same transformation model as for land data conversion and the relatively simpler concept of the model.

Using the estimated parameters in the Molodensky-Badekas transformation, the residuals, i.e., the difference between the observed coordinates in the new datum and coordinates obtained by applying the transformation with estimated parameters, are calculated for all 315 stations (Table 2). Overall, it appears that the parameter estimation was successful with coordinate biases less than 10 cm with standard deviations less than 55 cm.

When analyzing the residuals in regions, however, one can find considerable biases in the transformation results. For example, for the area of Jeju Island, it is shown that the residuals are considerably biased in the direction of east and north (Fig. 2). As mentioned before, the reason for this bias was considered to be the fact of nonequally distributed data used in the parameter estimation. In other words, the stations are densely distributed to the east and north relative to the location of Jeju Island, and this causes the estimated parameters to generate significant biases in those directions for the Jeju area. Therefore, the station distribution was optimized to mitigate the effect by network optimization algorithm, which comes in the next section.

4. STATION OPTIMIZATION

As seen in the previous section, using all 315 station coordinates to estimate the parameters for datum transfor-

Table 2. Residuals of the Molodensky-Badekas transformation for all 315 stations (Unit: m).

	ΔX	ΔY	ΔZ
Mean	0.000	−0.041	0.047
Std. Dev.	0.5236	0.4393	0.4165

Table 1. Estimated parameters with standard deviations for three similarity transformations.

Model		Tx (m)	Ty(m)	Tz (m)	Rx (arcsec)	Ry (arcsec)	Rz (arcsec)	Scale (ppm)
BW	Par.	−121.24	471.20	654.80	−1.62	2.03	1.92	8.17
	S.D.	0.986	0.746	0.871	0.025	0.030	0.029	0.010
MB	Par.	−146.84	504.34	685.66	−1.62	2.03	1.92	8.17
	S.D.	0.022	0.022	0.022	0.025	0.030	0.029	0.010
Veis	Par.	−146.84	504.34	685.66	−0.01	−0.01	−3.23	8.17
	S.D.	0.022	0.022	0.022	0.032	0.029	0.021	0.010

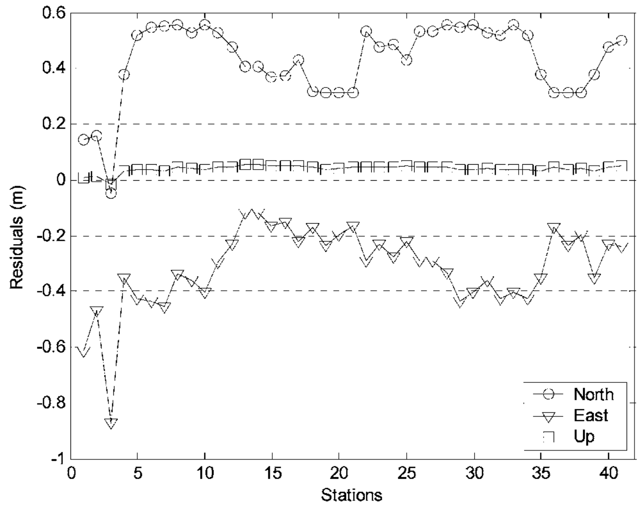

Fig. 2. Residuals on stations of Jeju Island after applying Molodensky-Badekas transformation with estimates from all available data.

mation caused significant biases in some areas because of the unequal distribution of the stations. Therefore, the station distribution should be optimized before the estimation of the transformation parameters.

For the optimization of the station distribution, the theory of network optimization can be implemented. The main objective of optimal design is to derive specifications for the necessary and sufficient accuracy of proposed set of observables given the desired accuracy of the unknown parameters (Vanicek and Karkiwsky, 1982). Following the objective, network optimization pursues high precision, reliability, and low cost. Here, these three components are not independent of each other, so the optimization problem can be redefined as a multivariate optimization problem (Schaffrin, 1985, p. 560).

$$\alpha_p(precision) + \alpha_r(reliability) + \alpha_c(cost)^{-1} = \max \tag{4}$$

where α_p, α_r, α_c represent weights for each component. Unfortunately, it is not easy to find the relative weights which satisfy all three components because of the high correlation among them. Therefore, optimization is usually considered to maximize the precision while maintaining the reliability and cost at certain levels.

According to Grafarend (1972), the conditions of the optimized network are the homogeneity and isotropy of the errors at each station. A network satisfying these two conditions is homogeneous, and consequently the error ellipses are circles of the same size. A variance-covariance matrix which is homogeneous and isotropic in an ideal network (called “criterion matrix”) possesses the Taylor-Karman structure (TK-structure), which defines the covariance between two points. It should be noted that this criterion matrix is independent of any linear models with specific rank-deficiency since the measurement type is not specified.

The Taylor-Karman structure defines the auto- and cross-covariance between two points in the network. The distance between two points P_i and P_j is defined as

$$s := |\underline{r}_i - \underline{r}_j| = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2 + (z_i - z_j)^2} \tag{5}$$

where $\underline{r}_i = (x_i, y_i, z_i)^T$ and $\underline{r}_j = (x_j, y_j, z_j)^T$ represent the Cartesian coordinates of P_i and P_j, respectively. Following Grafarend (1972), the general expression for the TK-structured criterion matrix between P_i and P_j is given by

$$\sigma_0^2 C_{ij} := \begin{bmatrix} \Sigma_m(s) & 0 & 0 \\ 0 & \Sigma_m(s) & 0 \\ 0 & 0 & \Sigma_m(s) \end{bmatrix} \tag{6}$$

$$+ [\Sigma_l(s) - \Sigma_m(s)] \cdot$$

$$\frac{1}{s^2}\begin{bmatrix} (x_i - x_j)^2 & (x_i - x_j)(y_i - y_j) & (x_i - x_j)(z_i - z_j) \\ (x_i - x_j)(y_i - y_j) & (y_i - y_j)^2 & (y_i - y_j)(z_i - z_j) \\ (x_i - x_j)(z_i - z_j) & (y_i - y_j)(z_i - z_j) & (z_i - z_j)^2 \end{bmatrix}$$

where $\Sigma_l(s)$ and $\Sigma_m(s)$ represent the longitudinal and cross-covariance functions, respectively, and σ_0^2 is the unit-free variance component. C denotes the ideal cofactor matrix of the estimated network point coordinates.

The above two covariance functions can be calculated using the analytical forms given by Grafarend and Schaffrin (1979):

$$\Sigma_l(s) = -\frac{4d^2}{s^2} + 2K_0(s/d) + \frac{4d}{s}K_1(s/d) + 2\frac{s}{d}K_1(s/d) \tag{7}$$

$$\Sigma_m(s) = +\frac{4d^2}{s^2} - 2K_0(s/d) - \frac{4d}{s}K_1(s/d) \tag{8}$$

where K_0 is the modified Bessel function of the second kind and zero order, K_1 is the modified Bessel function of the second kind and first order. The characteristic distance of the network, d, can be chosen by two suggestions below:

1) d should be chosen smaller than the minimum baseline in the network (Schmitt, 1980)

2) the maximum distance of the network is an upper bound for $10d$ (Wimmer, 1982).

Once the criterion matrix is computed using Equations 6 to 8, the weights of each measurement between stations can be estimated from the condition of minimum of the difference between the cofactor matrix $Q_{\hat{\xi}}$ of the estimated point coordinates $\hat{\xi}$, and an ideal criterion matrix (e.g., with TK-structure) C:

$$\|Q_{\hat{\xi}} - C\| = \min \tag{9}$$

Assuming uncorrelated observations in a Gauss-Markov

Model, $y = A\xi + e,\ e \sim (0,\ \sigma_0^2 P^{-1})$, this condition can be transformed into

$$\|A^T P A - C^{-1}\| = \min_{P:=diag\underline{p}} \tag{10}$$

where A is the design matrix, P is the weight matrix and C is a criterion matrix with TK-structure. After several steps of manipulation in the least squares sense, one can derive the normal equation for the weights:

$$(ACA^T * ACA^T)\hat{\underline{p}} = vecdiag(ACA^T) \tag{11}$$

where * now defines the Hadamard product of matrices with equal size, namely:

$$\underset{k\times l}{G} * \underset{k\times l}{H} = [g_{ij} \cdot h_{ij}]_{k\times l} \tag{12}$$

Based on the network optimization theory described above, one can sequentially select the stations which satisfy conditions of homogeneous and isotropic error ellipse. After applying the procedures, a total 42 stations out of 315 stations were selected as seen in Figure 3. It should be noted that the stations are almost equally distributed and the error ellipses more or less have equal size of circular shape.

Tables 3 and 4 show the estimated transformation parameters of the Molodensky-Badekas model with standard deviations using the data from the optimized 42 stations and residuals for all 315 stations, respectively. Comparing these to the corresponding Tables 1 and 2, one can notice that the overall precision and residuals are slightly poorer because of the small number of stations used in the adjustment. However, the residuals in regions show that the biases are considerably reduced as seen in the example of Jeju Island (see Figs. 3 and 4). Based on this uniformity and residual analysis, it is decided to select the Molodensky-Badekas model with the parameters in Table 3 as the datum transformation method for Korean ocean spatial data.

It should be mentioned that the transformation parameters for seas and islands should be independently estimated of land transformation parameters. The main reason for this is that the survey methods, data distribution, and data quality for land and sea data are different. The stations for land and sea area are not connected by a network in Korea. As mentioned above, the data used in this study was acquired through the campaign for the determination of a Korean territorial baseline. This assures the consistency in survey

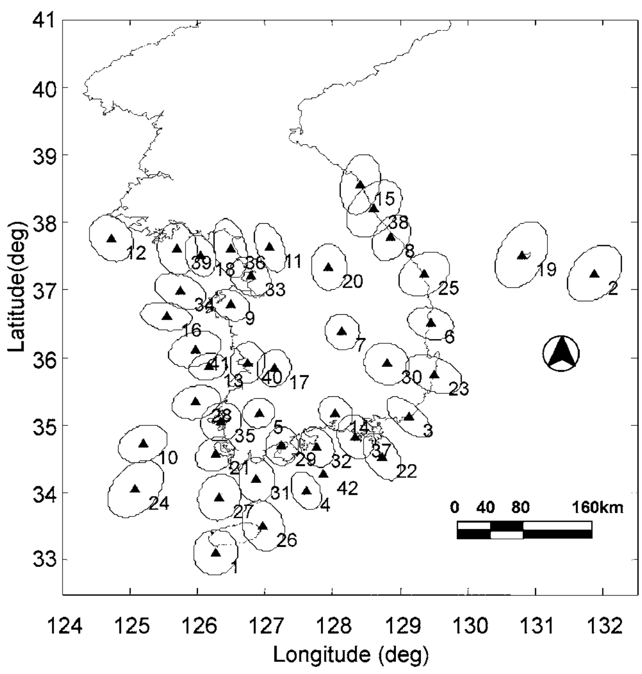

Fig. 3. Optimized station distribution with error ellipses.

Table 4. Residuals of the transformation using estimates calculated from optimized stations data only (Unit: m).

	ΔX	ΔY	ΔZ
Mean	0.101	0.076	0.028
Std. Dev.	0.532	0.475	0.443

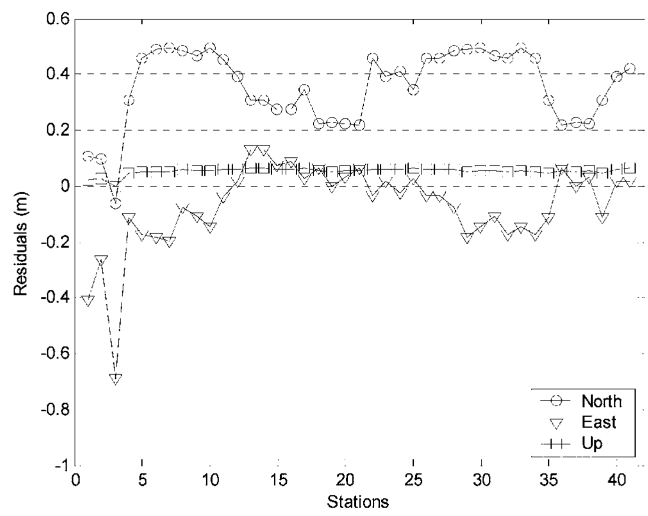

Fig. 4. Residuals on stations of Jeju Island after applying the Molodensky-Badekas transformation with estimates from optimized 42 stations of data.

Table 3. Estimated parameters of the Molodensky-Badekas model using optimized stations of data.

Parameters	Tx (m)	Ty (m)	Tz (m)	Rx (arcsec)	Ry (arcsec)	Rz (arcsec)	Scale (ppm)
Estimates	−145.36	504.49	686.80	−1.57	1.97	1.87	8.62
Std. Dev.	0.055	0.055	0.055	0.094	0.081	0.097	0.332

Table 5. Residuals of the transformation using land transformation parameters applied to the 42 selected stations (Unit: m).

	ΔX	ΔY	ΔZ
Mean	−0.449	0.623	−1.013
Std. Dev.	0.722	0.691	0.435

method and data quality so that the network of the stations is well-established. To ensure the necessity of the independent determination of the transformation parameters, the test results of applying the land transformation parameters from Yoon (2003) to the selected 42 stations are presented in Table 5. As one can expect, the biases and standard deviations of the residuals are much poorer than those in Table 4 which justifies the separate determination of transformation parameters for land and sea area.

5. DISTORTION CORRECTION

The similarity transformation is conformal which means that the transformation preserves the shape of objects such as line, curve, and polygon. If there is no distortion in coordinates from the old datum, the similarity transformation would be enough to obtain the coordinates in the new frame. If, however, there are distortions in old coordinates for some reason such as different surveying and adjustment methods, the similarity transformation would still leave significant residuals as in Figures 5 and 6. Therefore, the distortion should be corrected to achieve high accuracy in the datum transformation.

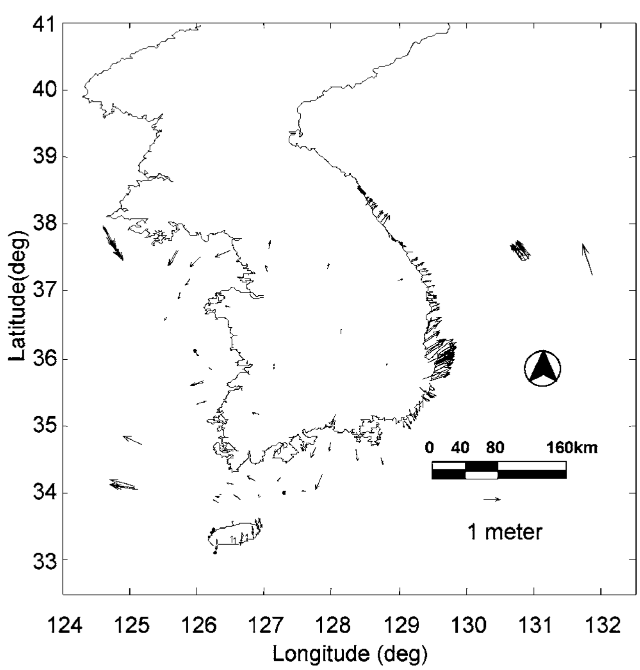

Fig. 5. The residuals of horizontal positions after the similarity transformation.

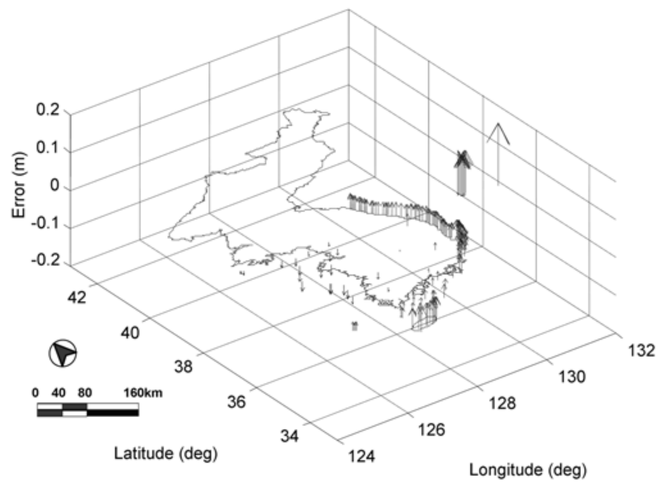

Fig. 6. The residuals of heights after the similarity transformation.

To correct the distortion, it has to be modeled and corrected with some mathematical methods such as multiple regression, least squares collocation, and surface fitting (Collier, 2002). Considering that the distortion can be complex and highly variable, simple surface fitting or regression might not be an appropriate method to correct it. In addition, it would be efficient to predict the distortions in grids, so that the distortion on a particular point can be interpolated using the values on the grids. Therefore, the least squares collocation (LSC) method has been applied to the coordinates produced from the similarity transformation to predict the distortions on regularized grids.

Figure 7 shows a brief schematic procedure to perform the distortion estimation using LSC. The first step in LSC estimation is to calculate the empirical autocorrelation based on the data, namely, the difference between the coordinates in the new datum and transformed ones using similarity transformation in this case. Then, an analytical covariance model

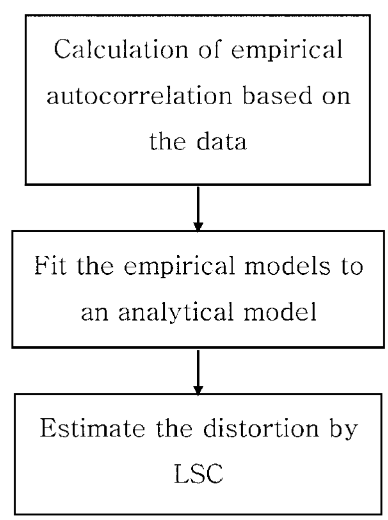

Fig. 7. Scheme of distortion estimation using LSC.

is selected in which parameters are estimated based on the calculated empirical values for all three components (latitude, longitude and height). Once the analytical functions are determined with proper parameters, those functions are used to predict distortions based on collocation theory.

It should be noted that LSC usually assumes ergodicity and isotropy. Ergodicity means that the probabilistic mean can be replaced by the spatial average for any of the realizations of the processes, and isotropy means the auto-covariance function which is independent of directions, i.e., it depends only on the distance between random variables.

$$C\{x(s), x(s+h)\} = C_x(\|h\|) \tag{13}$$

where $x(s)$ is a stochastic process at epoch/location s, and h is the distance between two processes.

To calculate the empirical autocorrelation, the data needs to be regularized so that data bins with an interval of 0.075 degree were constructed and the correlation values within each bin are averaged to produce the regularized correlation. Note that three components of the coordinates were separately treated to perform a one-dimensional autocorrelation computation. The data lag for the correlation was set to five degrees in all cases.

The selected analytical function for the autocorrelation of distortions in this study is the well-known Gaussian function given as:

$$C(\|h\|) = C_0 e^{-A^2 h^2} \tag{14}$$

where C is the covariance which depends only on the radial distance h between two points, A is the reducing factor, and C_0 is the variance. Based on the empirical autocorrelation calculated from data, the reducing factors and variances are estimated using least squares adjustment (Table 6). The degrees of fits for the analytical functions are shown in Figures 8 through 10. Note that the correlation of the height drops more rapidly than those of the other two components showing the roughness of the terrain.

Using the estimated parameters of the Gaussian function, the distortion at any point can be calculated using LSC:

$$x = C_s(C_l + D)^{-1} l \tag{15}$$

where x is the estimate, C_s is the cross-covariance between the observation and prediction points, C_l is the auto-covariance of observation points, D is the dispersion matrix for the observation error, and l is the observation. For details on the theory of LSC, see (Moritz, 1980).

Table 6. Estimated variance and reducing factor using empirical autocorrelation.

	Latitude	Longitude	Height
C_0 (deg^2)	2.477×10^{-11}	4.673×10^{-11}	1.195×10^{-3}
A (1/deg)	4.154	2.385	5.669

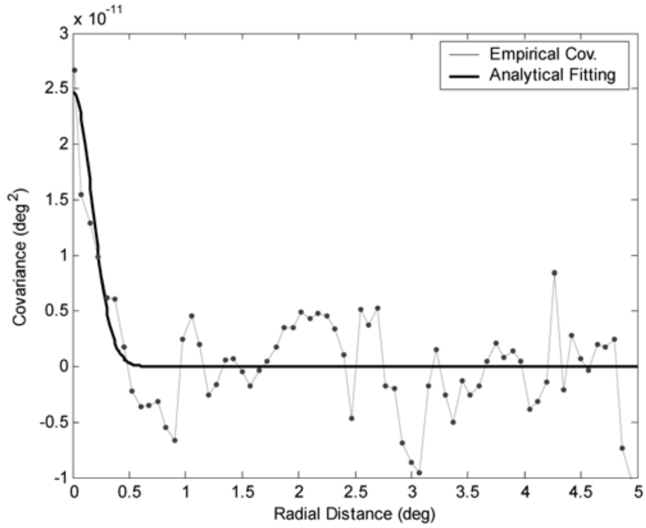

Fig. 8. Empirical and (fitted) analytical covariance functions for latitude.

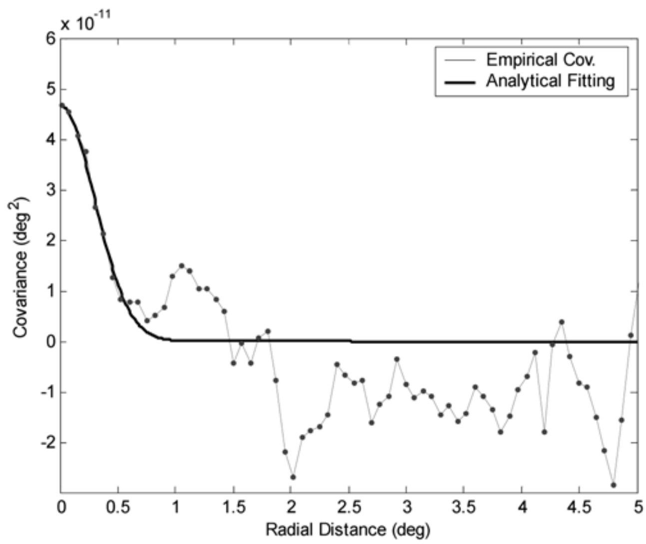

Fig. 9. Empirical and (fitted) analytical covariance functions for longitude.

As mentioned before, it is efficient to predict and save the distortions in grid form. In this study, the distortions are predicted and saved in 1′×1′ grids for latitudes of 33° to 39° and longitudes of 124° to 132°. Once the distortions are saved in a grid form, the distortion at an arbitrary point can be estimated using bilinear interpolation.

To check the accuracy of the distortion estimation, 165 points which have not been used for the calculation of transformation/distortions are selected. The statistics after applying the seven parameter transformation and distortion correction are shown in Table 7. As can be seen, the coordinate transformation was successfully performed with

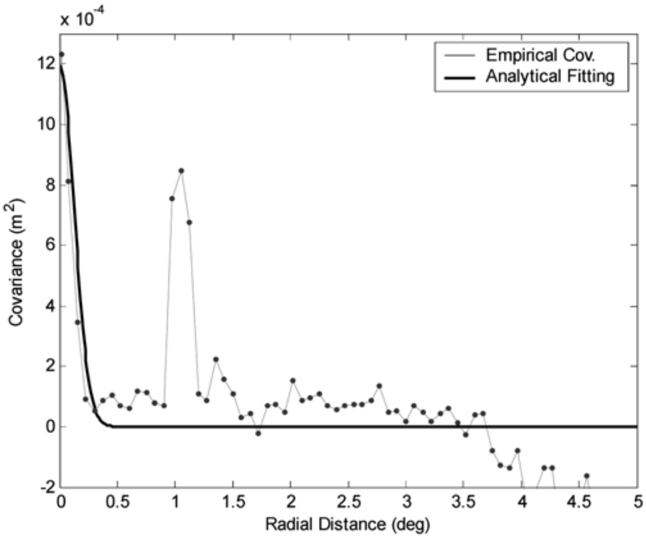

Fig. 10. Empirical and (fitted) analytical covariance functions for height.

Table 7. Statistics of transformation check with 165 check points (Unit: cm).

	Latitude	Longitude	Height
Mean (cm)	0.13	−1.02	0.44
Std. Dev. (cm)	11.39	12.86	0.64

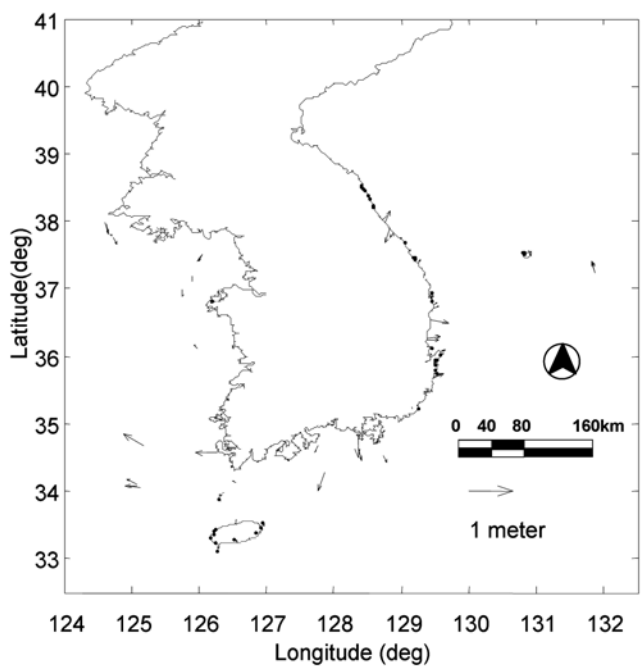

Fig. 11. The residuals of horizontal positions after the distortion correction.

biases less than 1.5 cm and standard deviations less than 15 cm. Overall trends shown in Figures 11 and 12 also confirm the successful transformation.

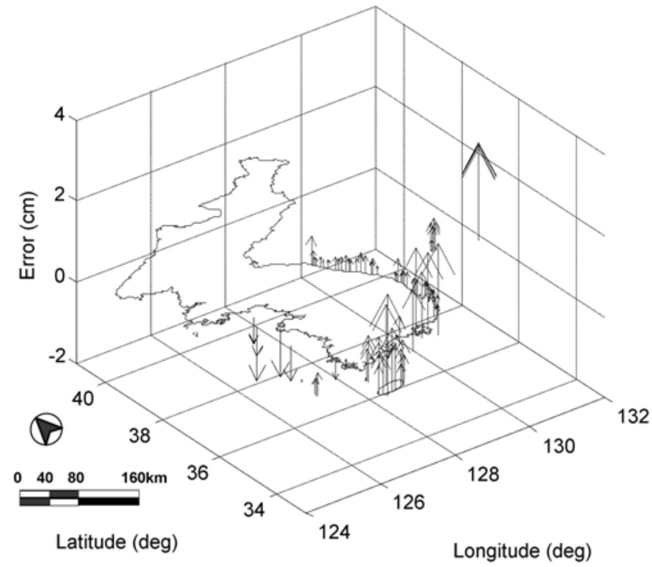

Fig. 12. The residuals of horizontal positions after the distortion correction.

6. CONCLUSIONS

For the datum transformation of Korean ocean spatial data, estimation of the parameters in three seven-parameter similarity transformation methods, the Bursa-Wolf, Molodensky-Badekas, and Veis models, are performed and analyzed. Based on the analyses and comparisons of those models, the Molodensky-Badekas model was selected.

To achieve high accuracy in the datum transformation, the station distribution was optimized using network optimization theory. It was found that the station optimization considerably contributes to eliminate the biases in the transformation achieving biases less than 10 cm with standard deviation less than 55 cm.

Further improvement on the transformation was achieved by modeling and predicting the distortions with least squares collocation. The predicted distortions are saved in 1′×1′ grids for all three components so that the distortion at an arbitrary point can be calculated with simple interpolation. The accuracy of the transformation was checked with 165 checkpoints and an overall accuracy better than 15 cm was achieved.

It is considered that this study could be a good example of conducting a datum transformation showing intensive data screening, station optimization, and distortion correction, so that it can be referenced by any national coordinate transformation task.

REFERENCES

Collier P. and J. Steed, 2001, Australia's National GDA94 Transformation Grids. 42nd Australian Surveyors Congress, Brisbane, Australia, Sept. 25–28.

Collier P., 2002, Development of Australia's National GDA94 Transformation Grids. Consultant's Report, Dept. of Geomatics, The University of Melbourne, Australia, 36p.

Grafarend, E., 1974, Optimization of Geodetic Networks. Canadian Surveyor, 28, 716–723.

Grafarend, E. and Schaffrin, B., 1979, Kriterion-Matrizen I – zweidimensionale homogene und isotrope geodätische Netze. Zeitschrift für Vermessungswesen, 104, 133–149.

Harvey B.R., 1986, Transformation of 3-D Coordinates. The Australian Surveyor, 32, 105–125.

Moritz, H., 1980, Advanced Physical Geodesy. Wichmann, Karlsruhe, 500p.

Rapp, R.H., 1993, Geometric Geodesy (Part II). The Ohio State University, Columbus, Ohio, 148 p.

Schaffrin, B., 1985, Network Design. In: Grafarend/Sansò (eds.), Optimization and Design of Geodetic Networks, Springer-Verlag, 548–597.

Schmitt, G., 1980, Second Order Design of Free Distance Networks Considering Different Types of Criterion Matrices. Bulletin Geodesique. 54, 531–543.

Vanicek, P., and Karkiwsky, E.J., 1982, Geodesy: The Concepts. North-Holland Publishing Company, New York, 691p.

Wimmer, H., 1982, Ein Beitrag zur Gewichtsoptimierung geodätischer Netze. Publ. DGK C-269, München, 254p.

Yoon, H., 2003, A Study on the datum transformation of digital maps (II) (Korean). Report 11-1500714-000002-01, Korean Institute of Geography, 120p.

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