Deformation Analysis Based on Designed Experiments and Kalman Filter

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ABSTRACT. This paper is focused on the deformation monitoring of survey control points in the Gidan Kwano main campus, Federal University of Technology, Minna, Nigeria. The main objectives are to develop and test a kinematic deformation analysis model using simulated GPS test data. RTK GPS was the main equipment deployed for the monitoring. The kinematic deformation analysis model developed for this study was based on Kalman filtering technique. In order to verify the developed kinematic model, designed experiments, with artificially introduced deformations, were performed to test centimetre-level horizontal movements on four points (GPS 01, GPS 08, GPS 09 and GPS 12). The developed kinematic model was used to determine six unknown parameters of movements, namely position displacements (dx, dy), velocities (Vx, Vy) and accelerations (ax, ay). The results of the computed movement parameters of the control points show that the introduced deformations were detected by the kinematic deformation model. The model also detected that there was no deformation introduced to point GPS 09. Some of the discrepancies in the computed results can be attributed to centring errors during observations.

Keywords: deformation monitoring, designed experiments, RTK GPS, Kalman filter, kinematic model.

1. Introduction

The classical task in deformation studies is the investigation of movements and displacements of an object with respect to space and time. Deformation studies cover a broad spectrum of applications ranging from the study of crustal deformation or tectonic movements, glacier and shelf ice movements at global or regional

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scale, to the deformation monitoring of engineered or natural structures such as dams, bridges, tunnels, landslides, etc. at local scale (Caspary 2000).

The primary goal of deformation studies is to investigate the spatial and temporal stability or displacements (the geometrical changes) of an object or body (Heunecke and Welsch 2000). As a result of technological advancement, which culminated in the development of new measurement and analysis tools, the emerging trend is to integrate the influencing or triggering forces, which caused the deformations, and the physical properties of the deforming object or body in the studies (Heunecke and Welsch 2000, Welsch and Heunecke 2001). Thus, the scope of deformation studies includes (Chrzanowski and Chen 1990, Szostak-Chrzanowski et al. 2008):

• Geometrical analysis, which describes the spatial and temporal changes a deformable body undergoes in its shapes, dimension and position. These changes or movements result when the deformable body (e.g., engineered or natural structure) is subjected to internal and external forces. The deformable body will experience failure when the movements, its velocity and/or acceleration exceed threshold values, usually determined using statistical hypothesis (Chrzanowski et al. 2007).

• Physical interpretation, which describes the relationship between the deformations and the factors causing the deformations. This relationship can be determined by statistical or deterministic method (Szostak-Chrzanowski et al. 2006). The statistical method analyses the relationship between the deformations and the causative factors, while the deterministic method includes the causative factors and the physical properties of the deforming body in the analysis. The results of the physical interpretation are useful for the development of predictive models, which when combined with the results of the geometrical analysis, gives a better understanding of the deformation process (Chrzanowski and Chen 1990).

Chen (1983) cited two reasons for the study of deformations. First is the practical reason which includes: checking the stability and/or instability of a structure, detection of symptoms of failure of a structure, and assessment of hazards resulting from failure of a structure. Secondly, the scientific reason which emphasises the need to develop new tools and techniques to foster a better understanding of the deformation phenomenon. The justification of these reasons is predicated on the huge human, economic and environmental losses caused by deformations of engineered and natural structures (The International Bank for Reconstruction and Development / The World Bank 2010). Deformation studies, therefore, is a vital tool for tackling the threats of artificial and natural disasters for the purposes of safety and protection of the population from hazards, efficient functioning of structures, environmental protection, and development of mitigation measures (Caspary 2000, Szostak-Chrzanowski et al. 2006).

This paper is focused on deformation monitoring of survey control points in the Gidan Kwano main campus, Federal University of Technology, Minna, Nigeria. The main objectives are to develop and test a kinematic deformation analysis model using simulated GPS test data. The kinematic deformation analysis model developed for this project was based on Kalman filtering technique. In order to verify the developed kinematic model, designed experiments, with artificially introduced deformations, were performed to test centimetre-level movements.

1.1. Problem Statement

The Federal University of Technology, Minna, Nigeria, established on 1st February 1983, moved to its permanent site at Gidan Kwano in the year 2005. In order to address the challenges of building infrastructures in the Gidan Kwano Campus, survey control points were established. Some of the infrastructures being developed include roads, lecture theatres, office complexes, and underground facilities such as pipelines and cables, among others. Over the years, there has been further extension of the control points within the university, to cope with the rapid development going on in the campus.

Due to the ongoing development projects in the campus, particularly those carried out underground, it is possible that deformation (or movement) might have occurred on this survey control points. The main challenge of this study, therefore, is to test the stability of some of the existing survey control points in the Gidan Kwano main campus.

1.2. Aim and Objectives

The main aim of this study is to develop a kinematic deformation model using Kalman filter for the detection of artificially induced deformation in designed experiments. In order to achieve this aim, the following objectives will be addressed:

- to design deformation monitoring experiments based on simulated RTK GPS observations,

- to develop a kinematic deformation analysis model using Kalman filter,

- to analyze the simulated/artificial deformations using the developed deformation model.

2. Kalman Filter in Deformation Analysis

One important task in deformation studies is to develop a data analysis technique for estimation: the process of extracting desired information from monitoring data in the presence of errors. Expectedly, GPS observations contain errors (Paar et al. 2011). If the GPS observations contain white noises, i.e. the errors are largely independent of each other; the standard least-squares method is suitable for parameter estimation. Apart from these uncorrelated white noises, some system model contains time-correlated coloured noises. In these cases, the main goal is to estimate the state of the system in the presence of measurement noises. The elements that describe the state of the system contain known and unknown information. Typically, the known information is utilised to compute the optimal estimates (unknown) of the system state. Theoretically, an optimal estimator is an algorithm that utilizes all measurement data to process the measurements in order to derive a minimum error estimate of the system state by using the prior knowledge of system and measurement dynamics, including the assumed statistics of system noise and measurement errors.

The least squares estimation method, a discovery ascribed to Carl Friedrich Gauss in 1795, is the first technique adopted for the estimation of unknown system state parameters from a series of noisy measurements (Grewal and Andrews 2008). However, one of the shortcomings of the least squares estimation method is in the fact that it cannot be used to address dynamic events which require the estimation of time-variant parameters, such as velocity and acceleration (Celik 1998). To handle dynamic problems, Kalman (1960) introduced a modified algorithm of the sequential least squares estimation method. Kalman modified least squares by (Krakiwsky 1975): 1) introducing a second model that captures the dynamic characteristics of each unknown parameters, thereby allowing the vector of parameters (state vector) to change with time, 2) adding a variance-covariance matrix on this secondary model; and 3) solving the problem sequentially or in parts. Based on these modifications, the main advantage of Kalman filter over the least squares is that it provides additional information to the system to allow the states to change with time. However, the differences between the least squares estimation and Kalman filter are minor. While least squares involve the minimising of the observation residuals (i.e. the difference between actual and predicted observations), the Kalman filter involves the minimising of the mean-square error of the solution (Petovello 2013).

The Kalman filter typically consists of two main components (Fig. 1), namely: a dynamic system and a series of measurements, obtained from noisy sensors. These two components are corrupted by white noises. The main task in Kalman filtering is the estimation of the unknown system state. The filter can accomplish this task without direct observation of the system or prior knowledge of the modelled system. Based on the noisy measurements of the process, the filter recursively minimizes the mean square estimation error to provide an optimal estimate of the system states and their uncertainties (Maybeck 1979).
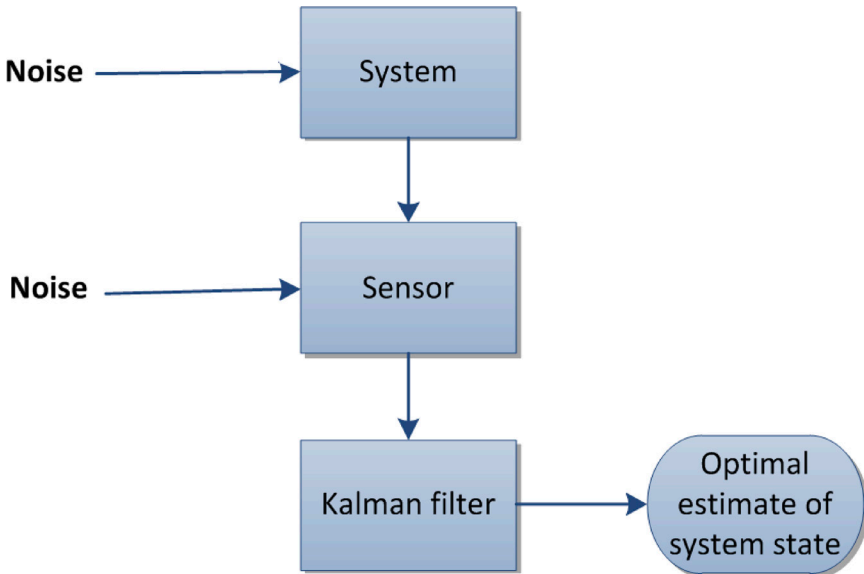

Fig. 1. *Kalman filter components (Maybeck 1979).*

The main advantages of Kalman filtering technique can be summarised as follows:

i) As a recursive data processing technique, the Kalman filter does not require all the past measurements and estimation to determine the current system state; only estimation from the previous step and the new input data are used. This makes the algorithm very suitable for processing a large quantity of data (Bogatin and Kogoj 2008).

ii) As an optimal linear estimator, the Kalman filter has the capability to uniquely determine the unknown system state and its test statistics in real-time. This makes the algorithm a useful tool to detect the differences between the model and the actual system state (Gamse et al. 2010).

iii) As an advanced analysis tool, the Kalman filter can be used to model noises present in observations; thereby allowing all the useful information present in the observations to be fully utilised (Liu et al. 2008).

The advantages of the Kalman filter can be utilised to carry out analysis of deformations caused by natural phenomenon such as earthquakes (Poyraz and Gülal 2007, Tu and Wang 2014). The Kalman filter has been widely used in the analysis and evaluation of kinematic measurements (Abousalem and McLellan 1994, Almagbile et al. 2010). Since its introduction (Kalman 1960), the Kalman filter has found practical application in the fields of kinematic positioning, integrated navigation systems, objects tracking, computer vision, image processing, process control systems, demographic estimation, stock price prediction, and data processing of deformation monitoring, among others (Welch and Bishop 2006, Delaney and Ward 2004, Wang 2008, Yuan et al. 2010).

Deformation analysis typically involves the estimation of a static set of unknown parameters, where each set of measurements is used to obtain a better estimate of the same quantities. In the real-time context, deformation monitoring requires knowledge of the present state of the deformable body rather than an overall average of all previous states. Kalman filter is an ideal technique for the analysis of deformation monitoring since it provides a summary picture of the current state of the unknown parameters.

In deformation studies, the data acquired from the monitored object or body contains both useful information and the noises. The main challenge in the deformation study, therefore, is how to effectively eliminate these noises and extract the useful deformation information, for accurate interpretation and prediction of the deformation process (Yuan et al. 2010). The Kalman filter model is one of the optimal techniques employed to process the GPS position time series in real-time (Brown and Hwang 1997, Grewal and Andrews 2008, Yang et al. 2001). The Kalman filter model has the capability to compute the optimal value of the state vector in the recursive least squares manner. The elements of the state vector in the Kalman filter model are the unknowns of the kinematic/dynamic system. These include the position of the object, and the variation of the position (velocity and acceleration). This property of the Kalman filter is vital for studying the behaviour of deformations (Ince and Sahin 2000).

2.1. Overview of Linear Kalman Filter Algorithm

The system and observation equations of the Kalman filter model are given by equations (1) and (2), respectively (Welch and Bishop 2006):

$$x_{k+1} = \Phi_k x_k + w_k \tag{1}$$

$$z_k = H_k x_k + v_k, \tag{2}$$

where x is the system state vector, Φ is the state transmission matrix, w is the system noise; z is the vector of observations, H is the measurement matrix, v is the measurement noise. The subscript k denote a quantity at time t_k.

The Kalman filter process consists of two sub-processes: the time update and the measurement update processes. The time update equations are given as follows (Brown and Hwang 1997):

$$\hat{x}_{k+1} = \Phi_k \hat{x}_k \tag{3}$$

$$P_{k+1}^- = \Phi_k P_k^- \Phi_k^T + Q_k, \tag{4}$$

where $\hat{x}_{k+1}$ is the predicted value of the state vector; $\hat{x}_k$ is the optimal estimate of the state vector at the previous epoch; P_{k+1}^- is the covariance of $\hat{x}_{k+1}$; P_k^- is the covariance of $\hat{x}_k$; and Q_k is the covariance of the system noise w_k. The measurement update equations are given as follows (Brown and Hwang 1997):

$$K_k = P_k^- H_k^T (H_k P_k^- H_k^T + R_k)^{-1} \tag{5}$$

$$V_k = z_k - H_k \hat{x}_{k+1} \tag{6}$$

$$Q_{V_k} = H_k P_k^- H_k^T + R_k \tag{7}$$

$$\hat{x}_{k+1} = \hat{x}_k + K_k V_k \tag{8}$$

$$P_{k+1}^- = (I - K_k V_k) P_k^-, \tag{9}$$

where K_k is Kalman gain matrix; R_k is covariance of the measurement noise; V_k is the innovation; and Q_{vt} is the covariance of innovation.

3. Deformation Monitoring Experiments

The study area is Gidan Kwano main campus of Federal University of Technology, Minna, Nigeria (see Fig. 2). The Federal University of Technology, Minna is a Federal Government owned university in Nigeria, established on 1st February 1983.

Field reconnaissance was carried out to choose the survey stations to be monitored. Five survey stations were selected for this study, namely: GPS01, GPS08, GPS09, GPS10, and GPS12 (see Fig. 3). GPS10 was chosen to be the base station. The coordinates of the survey stations were obtained from the Department of Surveying & Geoinformatics, Federal University of Technology, Minna. On each of

Fig. 2. *Part of Gidan Kwano Campus, Minna, Nigeria.*

the survey stations (except GPS 09), artificial deformations were introduced as physical movements of GPS antenna.

Fig. 3. *Up – from left GPS 01, GPS 08 and GPS 09; down – from left GPS 10, GPS 12 and base station setup.*

The primary goal of the designed experiments was to test the capability of the developed kinematic deformation model to detect centimetre-level movements. In the experiments, a HI-Target RTK GPS (dual frequency) was used to monitor the movements of 4 points: GPS 01, GPS 08, GPS 09 and GPS 12. Using the Hi-Target GPS, the coordinates (x, y), consisting of 10 series of observations for each of the 4 points were determined for each epoch. After determining these coordinates, artificial deformations were introduced to the points as follows (see Table 1, Figs. 4 and 5): GPS 01 (1 cm deformation was introduced to the northing and easting, respectively in each of the 4 epochs of observations); GPS 08 (1 cm deformation was introduced to the northing in each of the 4 epochs of observations); GPS 09 (no deformations was introduced); and GPS 12 (1 cm deformation was introduced to the easting in each of the 4 epochs of observations). The time interval between epochs of the simulated data was assumed to be 3 months.

Table 1. *Designed experiments showing artificially introduced deformations (*ND = No Deformation).*

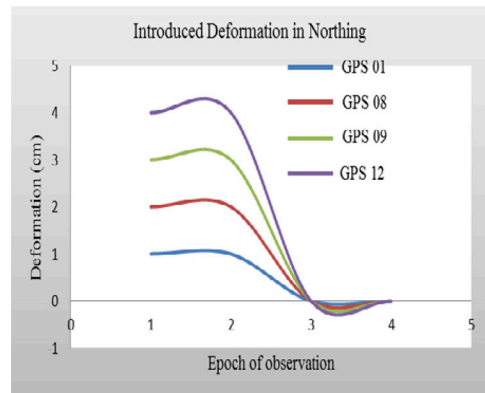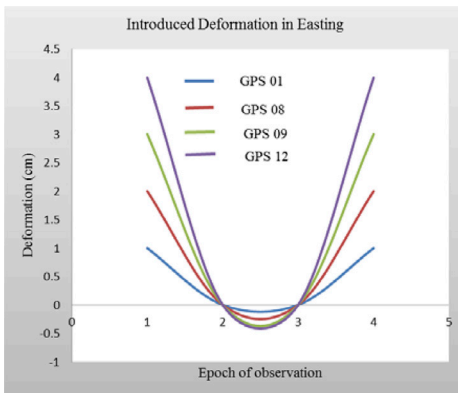| Point	Epoch1	Epoch1	Epoch2	Epoch2	Epoch3	Epoch3	Epoch4	Epoch4
	Easting	*Northing*	*Easting*	*Northing*	*Easting*	*Northing*	*Easting*	*Northing*
GPS 01	1 cm	1 cm	2 cm	2 cm	3 cm	3 cm	4 cm	4 cm
GPS 08	*ND	1 cm	*ND	2 cm	*ND	3 cm	*ND	4 cm
GPS 09	*ND	*ND	*ND	*ND	*ND	*ND	*ND	*ND
GPS 12	1 cm	*ND	2 cm	*ND	3 cm	*ND	4 cm	*ND

Fig. 4. *Introduced deformation in Easting.* Fig. 5. *Introduced deformation in Northing.*

4. Kalman Filtering Model for Deformation Analysis

Using the quadratic polynomial function (Welsch and Heunecke 2001), a time-de-pendent 3D kinematic model consisting of position, velocity and acceleration of monitored points can be formed and applied to GPS survey data as (Holdahl and Hardy 1979, Yalcinkaya and Bayrak 2005, Acar et al. 2008):

$$X_{k+1} = X_k + (t_{k+1} - t_k)V_{Xk} + \frac{1}{2}(t_{k+1} - t_k)^2 a_{Xk}$$

$$Y_{k+1} = Y_k + (t_{k+1} - t_k)V_{Yk} + \frac{1}{2}(t_{k+1} - t_k)^2 a_{Yk} \qquad (10)$$

$$Z_{k+1} = Z_k + (t_{k+1} - t_k)V_{Zk} + \frac{1}{2}(t_{k+1} - t_k)^2 a_{Zk}$$

where X_k, Y_k, Z_k is adjusted point coordinates at period k; V_{Xk}, V_{Yk}, V_{Zk} is velocity of point coordinates; a_{Xk}, a_{Yk}, a_{Zk} is acceleration of point coordinates.

The matrix form of the kinematic model in Equation (10) can be represented as:

$$\bar{Y}_k = \begin{bmatrix} X \\ Y \\ Z \\ V_X \\ V_Y \\ V_Z \\ a_X \\ a_Y \\ a_Z \end{bmatrix}_{k+1} = \begin{bmatrix} I & I(t_{k+1}-t_k) & I\dfrac{(t_{k+1}-t_k)^2}{2} \\ 0 & I & I(t_{k+1}-t_k) \\ 0 & 0 & I \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ V_X \\ V_Y \\ V_Z \\ a_X \\ a_Y \\ a_Z \end{bmatrix}_k + \begin{bmatrix} I\dfrac{(t_{k+1}-t_k)^2}{2} \\ I(t_{k+1}-t_k) \\ I \end{bmatrix}_{k,k+1} w_k \quad (11)$$

$$\bar{Y}_k = T_{k,k+1}\hat{Y}_k, \qquad (12)$$

where $\bar{Y}_k$ (16,1) is the predicted state vector (position, velocity and acceleration) at period k (current time); $\hat{Y}_k$ (16,1) is the predicted state vector at preceding time; $T_{k,k+1}$ (16,16) is the transition matrix; I is the unit matrix.

The Kalman filtering prediction step at period k and its covariance matrix can be written as Equations (13) and (14):

$$\bar{Y}_k = T_{k,k+1}\hat{Y}_k + N_{k,k+1}w_k \qquad (13)$$

$$Q_{\bar{Y}\bar{Y},k} = T_{k,k+1}Q_{\hat{Y}\hat{Y},k}T_{k,k+1}^T + N_{k,k+1}Q_{ww,k}N_{k,k+1}^T, \qquad (14)$$

where $N_{k,k+1}$ is the system noise matrix; w_k is the random noise vector at period k; $Q_{\hat{Y}\hat{Y},k}$ is the covariance matrix at preceding time; $Q_{ww,k}$ is the covariance matrix of system noise.

The adjustment of the kinematic model can be given in matrix form in Equations (15) and (16). Equation (16) is the functional model for the Kalman filtering procedure. The stochastic model for the Kalman filtering procedure is given in Equation (17):

$$V_k = z_k - H_k \hat{x}_{k+1} \tag{15}$$

$$\begin{bmatrix} \bar{Y}_k \\ I_k \end{bmatrix} = \begin{bmatrix} I \\ A_k \end{bmatrix} \hat{Y}_k - \begin{bmatrix} V_{\bar{Y},k} \\ V_{L,k} \end{bmatrix} \tag{16}$$

$$Q_k = \begin{bmatrix} Q_{\bar{Y}\bar{Y},k} & 0 \\ 0 & Q_{LL,k} \end{bmatrix}, \tag{17}$$

where V_k is the innovation vector; z_k is the actual observation; $H_k \hat{x}_{k+1}$ is the predicted observation.

The kinematic model using Equations (16) and (17) were solved and their movement parameters (positions, velocities and accelerations) were computed with two periods of observations.

5. Results and Analysis

In the kinematic model, movement parameters are point displacements, velocities and accelerations. The movement parameters were solved based on Kalman filtering technique, using two periods of measurements, which were sufficient to solve movement parameters using the model. Three months was adopted as the time interval between periods of measurements. Only horizontal movements are considered in this paper as artificial deformations were introduced only to the horizontal coordinates.

The kinematic model deformation results are given in Tables 2–6. The first stage of the kinematic model deformation results was computed using epoch 1–2 simulated data. The results of the computed movement parameters (positions and velocities) are given in Tables 2 and 3. The second stage of the kinematic model deformation results was computed using epoch 1–3 simulated data. The results of the computed movement parameters (positions, velocities and accelerations) are given in Tables 4–6. In the kinematic model, dx and dy are the computed position movement parameters in the Easting and Northing, respectively; Vx and Vy are the computed velocity movement parameters in the Easting and Northing, respectively; ax and ay are the computed acceleration movement parameters in the Easting and Northing, respectively. The critical values (Tdx, Tdy – for positions in Easting and Northing, respectively; Tvx, Tvy – for velocities in Easting and Northing, respectively; Tax, Tay – for accelerations in Easting and Northing, respectively) were computed and compared to the t-distribution table values (qt) to ascertain whether the movement parameters were significant or not. If the movement parameters (dx, dy; Vx, Vy; and ax, ay) at the specified confidence level ($\infty = 0.05$) have significantly changed (unstable), a (+) sign is given; otherwise (stable), a (–) sign is given.

Table 2. *Kinematic model deformation results (Epoch 1–2) – Position.*

Position (dx, dy) If T > qt then (+) ''unstable'' If T < qt then (–) ''stable'' Critical value: T (Tdx, Tdy); Test values for decision (qt = 2.04)				
Points	**GPS 01**	**GPS 08**	**GPS 09**	**GPS 12**
dx (cm)	0.96	–0.644	–0.078	0.387
Tdx	10.45(+)	6.70(+)	0.67(–)	7.06(+)
Decision	unstable	unstable	stable	unstable
dy (cm)	–2.01	1.502	–0.059	–1.731
Tdy	29.25(+)	15.58(+)	0.51 (–)	39.02(+)
Decision	unstable	unstable	stable	unstable

In GPS 01, artificial deformation of 1 cm was introduced to Easting and Northing coordinates. The kinematic model detected movements of 0.96 cm in Easting and –2.01 cm in Northing. In GPS 08, artificial deformation of 1 cm was introduced to Northing, and the model detected movement of 1.502 cm. In GPS 12, artificial deformation of 1 cm was introduced to Easting, and the model detected movement of 0.387 cm. No artificial deformation was introduced to GPS 09. The discrepancies in the kinematic model results can be attributed to centring errors during observations.

Table 3. *Kinematic model deformation results (Epoch 1–2) – Velocity.*

Velocity (Vx, Vy) If T > qt then (+) ''unstable'' If T < qt then (–) ''stable'' Critical value: T (Tdx, Tdy); Test values for decision (qt = 2.04)				
Points	**GPS 01**	**GPS 08**	**GPS 09**	**GPS 12**
Vx (cm/month)	0.316	–0.213	–0.021	0.126
Tvx	7.30(+)	4.72(+)	0.33(–)	4.93(+)
Decision	unstable	unstable	stable	unstable
Vy (cm/month)	–0.670	0.500	–0.016	–0.576
Tvy	20.20(+)	11.00(+)	0.29(–)	27.58(+)
Decision	unstable	unstable	stable	unstable

The computed velocities of movements using the kinematic model in GPS 01 are 0.316 cm/month for Easting (expected value is 0.333 cm/month, i.e. 1 cm divided by 3 months interval) and –0.670 cm/month for Northing (expected value is 0.333 cm/month). The computed velocity of movement in GPS 08 is 0.5 cm/month (expected value is 0.333 cm/month). The computed velocity of movement in GPS 12 is 0.126 cm/month (expected value is 0.333 cm/month).

Table 4. *Kinematic model deformation results (Epoch 1–3) – Position*.

Position (dx, dy) If T > qt then (+) ''unstable'' If T < qt then (–) ''stable'' Critical value: T (Tdx, Tdy); Test values for decision (qt = 2.04)				
Points	**GPS 01**	**GPS 08**	**GPS 09**	**GPS 12**
dx (cm)	1.544	–0.867	–0.495	1.309
Tdx	21.94(+)	12.59(+)	3.85(+)	20.58(+)
Decision	unstable	unstable	unstable	unstable
dy (cm)	–2.354	2.152	–0.125	–1.764
Tdy	44.56(+)	31.18(+)	1.40(–)	34.57(+)
Decision	unstable	unstable	stable	unstable

In GPS 01, artificial deformation of 3 cm was introduced to Easting and Northing coordinates (Epoch 1–3). The kinematic model detected movements of 1.544 cm in Easting and –2.354 cm in Northing. In GPS 08, artificial deformation of 3 cm was introduced to Northing, and the model detected movement of 2.152 cm. In GPS 12, artificial deformation of 3 cm was introduced to Easting, and the model detected movement of 1.309 cm. No artificial deformation was introduced to GPS 09. The discrepancies in the kinematic model results can be attributed to centring errors during observations.

Table 5. *Kinematic model deformation results (Epoch 1–3) – Velocity*.

Velocity (Vx, Vy) If T > qt then (+) ''unstable'' If T < qt then (–) ''stable'' Critical value: T (Tdx, Tdy); Test values for decision (qt = 2.04)				
Points	**GPS 01**	**GPS 08**	**GPS 09**	**GPS 12**
Vx (cm/month)	0.508	–0.284	–0.088	0.421
Tvx	9.01(+)	5.27(+)	2.72(+)	8.52(+)
Decision	unstable	unstable	unstable	unstable
Vy (cm/month)	–0.784	0.715	–0.026	–0.587
Tvy	18.08(+)	12.79(+)	0.98(–)	14.13(+)
Decision	unstable	unstable	stable	unstable

The computed velocities of movements in GPS 01 are 0.508 cm/month for Easting (expected value is 0.5 cm/month, i.e. 3 cm deformation divided by 6 months interval) and –0.784 cm/month for Northing (expected value is 0.5 cm/month). The computed velocity of movement in GPS 08 is 0.715 cm/month (expected value is 0.5 cm/month). The computed velocity of movement in GPS 12 is 0.421 cm/month (expected value is 0.5 cm/month).

Table 6. *Kinematic model deformation results (Epoch 1–3) – Acceleration.*

Acceleration (ax, ay) If T > qt then (+) ''unstable'' If T < qt then (–) ''stable'' Critical value: T (Tdx, Tdy); Test values for decision (qt = 2.04)				
Points	**GPS 01**	**GPS 08**	**GPS 09**	**GPS 12**
ax (cm/month^2)	0.032	–0.011	–0.003	0.048
Tax	2.20(+)	0.84(–)	0.44(–)	3.82(+)
Decision	unstable	stable	stable	unstable
ay (cm/month^2)	–0.019	0.036	0.000	–0.002
Tay	1.71(–)	2.50(–)	0.08(–)	0.18(–)
Decision	stable	unstable	stable	stable

The computed accelerations of movements in GPS 01 are 0.032 cm/month^2 for Easting (expected value is 0.083 cm/month^2, i.e. 3 cm deformation divided by 6^2 months interval) and –0.019 cm/month^2 for Northing (expected value is 0.083 cm/month^2). The computed velocity of movement in GPS 08 is 0.036 cm/month^2 (expected value is 0.083 cm/month^2). The computed velocity of movement in GPS 12 is 0.048 cm/month^2 (expected value is 0.083 cm/month^2).

The kinematic model was utilized to determine six unknown parameters, namely position displacements (dx, dy), velocities (Vx, Vy) and accelerations (ax, ay). The position displacements were computed using the difference between coordinates obtained from two observation periods. The velocities of the movements were computed by dividing the position displacement vector with the time interval between two observation periods. Also, the accelerations of movements were computed by dividing the position displacement vector by the squares of time interval between two observation periods. The results of the computed movement parameters for points in Tables 2–6 above show that the introduced deformations were detected by the kinematic deformation model. The model also detected that there was no deformation introduced to point GPS 09. Some of the discrepancies in the computed results can be attributed to centring errors during observations.

6. Conclusion

The deformation in survey control points will possibly affect all survey works based on those control points. Deformation monitoring experiments were carried out to ascertain the stability (or otherwise) of survey control points in the Gidan Kwano main campus, Federal University of Technology, Minna, Nigeria. The main aim of the study was to develop a kinematic deformation model for the detection of artificially introduced deformations in designed experiments. The deformation solutions in this study were realized based on a combined epoch solution approach, using the Kalman filtering technique. In the simulated deformation monitoring experiments, different scenarios of case studies were used to test centimetre-level horizontal movements of four survey control points. The developed kinematic model was em-

ployed to determine six unknown parameters, namely position displacements (dx, dy), velocities (Vx, Vy) and accelerations (ax, ay). The results of the computed movement parameters of the control points show that the introduced deformations were detected by the kinematic deformation model. Some of the discrepancies in the computed results can be attributed to centring errors during observations.

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Primjena deformacijske analize i Kalman filtera na simuliranim podacima mjerenja

SAŽETAK. U radu je opisano određivanje deformacija kontrolnih točaka u glavnom kampusu Gidan Kwano, Federal University of Technology, Minna, u Nigeriji. Glavni su ciljevi razviti i ispitati kinematički model deformacijske analize primjenom simuliranih GPS-testnih podataka. Za određivanje deformacija primijenjena je mjerna metoda RTK GPS. Kinematički model deformacijske analize razvijen za ovo istraživanje temelji se na tehnici Kalman filtriranja. Kako bi se ispitao razvijen kinematički model, simulirani su podaci mjerenja s umjetno uvedenim deformacijama, koji su poslužili za ispitivanje horizontalnih pomaka na centimetarskoj razini na četiri točke (GPS 01, GPS 08, GPS 09 i GPS 12). Razvijeni kinematički model koristi se za određivanje šest nepoznatih parametara pomaka, tj. položajnih pomaka (dx, dy), brzina (Vx, Vy) i ubrzanja (ax, ay). Rezultati izračunatih parametara pomaka kontrolnih točaka pokazuju da su uvedene deformacije detektirane kinematičkim deformacijskim modelom. Model je također detektirao da nema deformacije uvedene na točki GPS 09. Pojedina odstupanja u izračunatim rezultatima mogu se pripisati pogreškama centriranja prilikom opažanja.

Ključne riječi: određivanje deformacije, simulirani podaci mjerenja, RTK GPS, Kalman filter, kinematički model.