Automatic Detection and Analysis of Offsets in GNSS Position Time Series Using RMS Sliding-Window Method and Synthetic Model

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Abstract

This paper presents a method for automatically detecting and analyzing offsets in GNSS (Global Navigation Satellite System) position time series using the RMS (Root Mean Square) sliding-window approach. This technique identifies anomalies that indicate offsets within the time series. To adjust parameters such as linear trends, seasonal signals, and offsets accurately, synthetic model of GNSS position time series is utilized. The method is implemented in an automated program, pygps_ts, programmed by Python. The effectiveness of this approach is validated using both synthetic and real data from CORS (Continuously Operating Reference Station) stations in Vietnam. The results show that the program can accurately and efficiently detect and analyze offsets, identifying the epochs and magnitudes of these offsets in various scenarios. This study offers a practical tool for GNSS data processing, which is especially useful for tectonic studies and geodetic applications in Vietnam, where the continuous GNSS network is still developing. The study demonstrates the potential of this method for broader applications in monitoring and analyzing GNSS data in different regions. s accuracy and efficiency in offset detection and analysis.

Keywords: *GNSS position time series, displacement tectonic, offset, sliding-window, CORS*

1. Introduction

In recent decades, the Global Navigation Satellite System (GNSS) has emerged as an indispensable tool in the field of geodetic monitoring of Earth's crustal movements. Continuous GNSS stations, campaign GNSS stations, and continuously operating reference stations (CORS) observe signals from GNSS satellites [1], including USA's GPS, Russia's GLONASS, Europe's Galileo, Japan's QZSS, and China's BeiDou, enabling the generation of position time series for monitoring stations. With the advantage of continuous data and dense observation stations, these networks of GNSS stations facilitates the monitoring and analysis of both short-term and long-term variations in Earth's crust with millimeter-level accuracy [2]. These data are processed and analyzed to determine temporal displacements, including linear displacement, seasonal variations, and offsets due to earthquakes, land subsidence, or other geological phenomena. This information is crucial for earthquake forecasting and understanding the processes occurring within the Earth [3–5].

In processing and analyzing GNSS position time series using geodetic methods, determining a mathematical model to comprehensively describe the recorded phenomena is crucial. This approach helps in accurately and thoroughly identifying the movement parameters of the GNSS stations for various research purposes [6–9]. For GNSS stations monitoring crustal displacement in Vietnam, the recorded phenomena primarily include linear trends, periodic movements, and offsets (or jumps) in the position time series [7, 10–12]. These offsets can be caused by various factors, such as tectonic activities like earthquakes, or technical issues like station location changes, antenna changes, or other technical errors. These offsets significantly impact the accuracy of movement parameter estimates in the GNSS position time series if they are not detected and corrected [7, 13–16].

In the study on offset detection in GPS coordinate time series, Amiri-Simkooei et al. [6] developed a method using a functional model (including linear trends and periodic signals) and a stochastic model (including white noise and colored noise). By integrating both models, the offset detection method becomes more effective, improving the accuracy of GPS time series analysis and interpretation. Bruni et al. [17] applied the Sequential t-test Analysis of Regime Shifts method to identify the epoch and magnitude of offset in GNSS data sets, showing that the offsets identified are split into 48% true-positive, 28% false-positive, and 24% false-negative events with synthetic data. This method was successfully applied to a GPS time series spanning over 15 years in the Po Plain, Italy, and was validated as effective when compared with other observational techniques. Khazraei & Amiri-Simkooei [18] investigated improving the performance of the offset detection method in GNSS time series using a spline function, referred to as As-mode. The GNSS coordinate time series, including linear trends, seasonal signals, jumps, and white noise combined with colored noise, were simulated to compare performance. The results indicated a significant improvement in the overall performance of the algorithm, with the true positive detection rate increasing to 61.1%. Additionally, in 90% of cases, the velocities of the stations were estimated with an error of only 0.8 mm/year compared to the simulated values. A novel approach in GNSS position time series analysis involves the application of machine learning techniques for offset detection. Crocetti et al. [16] utilized ten machine learning algorithms to identify offsets in series attributed to seismic events in Japan. The results demonstrate

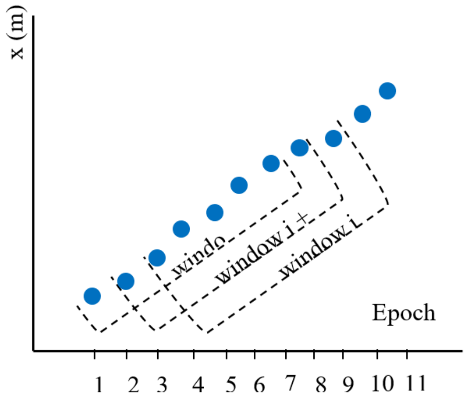


Fig. 1. Sliding-windows in GNSS position time series
Rys. 1. Przesuwne okna w szeregach czasowych pozycji GNSS

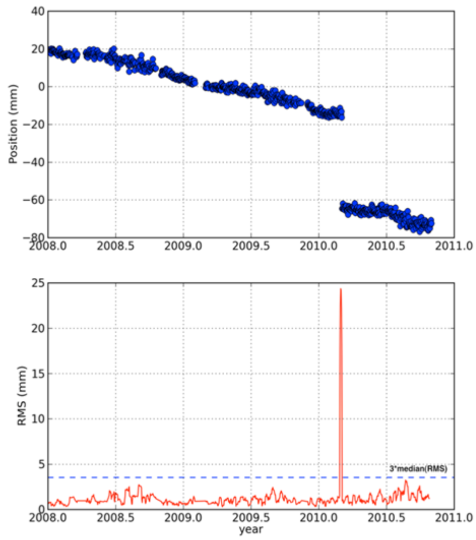


Fig. 2. The relationship between the offset and the RMS of the sliding-widow [22]
Rys. 2. Zależność przesunięcia od wartości skutecznej okna przesuwnego [22]

that the Random Forest method yielded the highest performance, though it only attained an F1 score of 0.77, a recall of 0.78, and a precision of 0.76.

In Vietnam, the application of GNSS in crustal displacement monitoring has been initiated and is in its early stages. GNSS data processing is largely conducted using softwares such as Gamit/GLOBK [19] or Bernese Bernese [20] with limited research on GNSS position time series analyzing. In a study on absolute displacements in the Tam Dao region, Vy Quoc Hai et al. [21] processed data of 6 mesurement cycles in 1996 and 2006 of GPS network using GPSurvey and Bernese software to determine the displacements of observation stations. Due to the availability of coordinate data at only 6 epochs, the motion of the observation stations was described using linear trend function.

In studies conducted by Tran et al. [7, 12], the authors processed data from the network of CORS stations across the territory of Vietnam to determine the velocity vector field. The daily GNSS position time series obtained were processed using a comprehensive motion model including linear trends, seasonal signals, and offsets. However, the epoch of the offsets was not automatically determined.

Thus, it is evident that in Vietnam, study on analyzing and processing the GNSS position time series to determine crustal displacement parameters is still limited, representing early-stage investigations. Studies in this field are crucial, particularly in light of the operationalization of the Vietnamese national satellite positioning network (VNGEONET) which is anticipated to catalyze continuous GNSS applications in Earth science research. Moreover, both globally and in Vietnam, continuous GNSS networks are expanding spatially, leading to an accumulation of increasingly voluminous data over time. Consequently, processing the position time series of these continuous GNSS networks will encounter challenges associated with large and complex datasets. Therefore, it is essential to study the application of algorithms and computational tools to facilitate swift, robust, and accurate analysis of GNSS position time series.

This paper focuses on developing a method for the automatic detection and analysis of offsets in GNSS position time series. The method utilizes an RMS (Root Mean Square) sliding-window approach to analyze consecutive coordinates within the time series. Subsequently, a synthetic model of the GNSS position time series is employed to accurately adjust the parameters of the model, including linear trends, seasonal signals, and offsets, which are common and significant phenomena at continuous GNSS stations in Vietnam. The

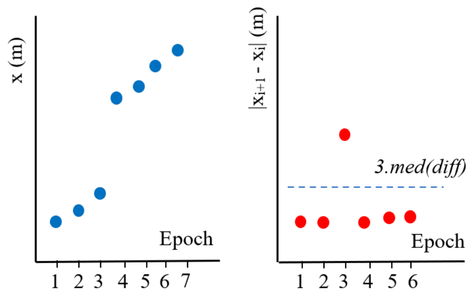


Fig. 3. Detecting the location of the offset in the sliding-window with anomalous RMS value
Rys. 3. Wykrywanie położenia przesunięcia w oknie przesuwnym z nieprawidłową wartością RMS

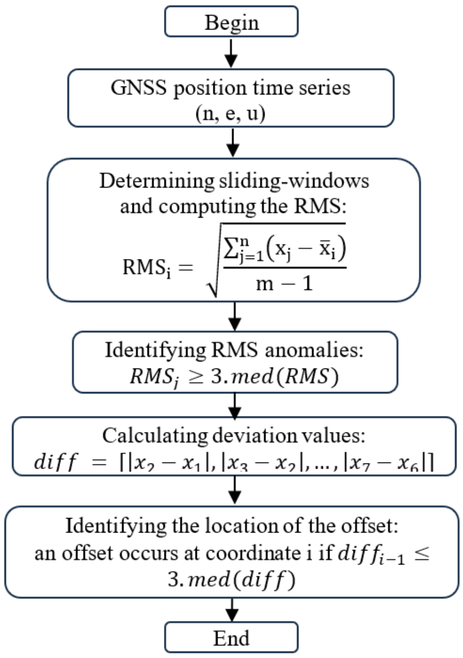


Fig. 4. Detecting the offsets in the GNSS position time series
Rys. 4. Wykrywanie przesunięć w szeregach czasowych pozycji GNSS

method is then implemented as an automated GNSS position time series analysis program using the Python programming language. The method and the developed program are tested using both simulated data and actual data from two CORS stations of the TAST network in Vietnam.

2. Methodology

2.1. RMS sliding-window method for offset detection

This method relies on the variation of the root mean square (RMS) of adjacent coordinates within a temporal window of GNSS position time series to detect offsets [22]. An anomaly is indicated when the RMS value of a corresponding window exceeds a threshold, indicating that this window contains an offset.

Sliding-window determination and RMS anomaly indentification:

Sliding-windows are determined by spanning consecutive coordinates within the time series. For instance, for a component coordinate $\{x_1, x_2, \ldots, x_n\}$, the first window spans from x_1 to x_{1+m}, the second window from x_2 to $x_{2+m}, \ldots$), and so forth, until the last coordinate (see Figure 1). Thus, with n coordinates, there are n-1 sliding-windows.

The RMS value for each window is computed using the formula (1):

$$RMS_i = \sqrt{\frac{\sum_{j=1}^{n}(x_j - \bar{x}_i)}{m-1}} \quad (1)$$

where x_j is the j-th coordinate of the i-th window, and $\bar{x}_i$ is the average coordinate of n coordinates in the i-th window.

The number of coordinates in the sliding window, denoted by m, is chosen to balance statistical significance and sensitivity to offsets. Here, m = 7 meets these criteria based on experimentation.

The threshold for indentifying RMS anomalies is set at 3 times the median value of RMS values, corresponding to a 99% confidence level [23], denoted as ε as per Formula (2):

$$\varepsilon = 3.med(RMS) \quad (2)$$

where med(RMS) represents the median of RMS values.

Figure 2 illustrates the relationship between the offset and the RMS of the sliding window. In Figure 2, the upper plot represents a time series of coordinates (green dots) from 2008 to 2011, exhibiting an offset at epoch 2010.175. The lower plot represents the RMS series of corresponding sliding-windows (red line), with anomaly RMS values corresponding to the

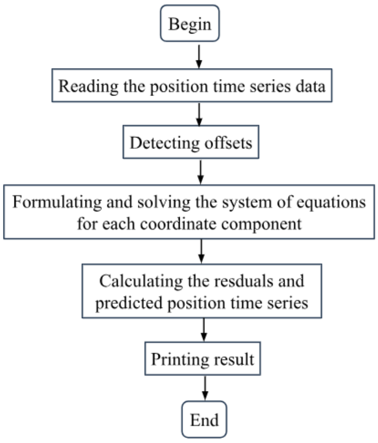


Fig. 5. Algorithm flowchart of pygps_ts program
Rys. 5. Schemat działania algorytmu programu pygps_ts

Tab. 1. Adjusted and design parameters of synthetic data
Tab. 1. Parametry korygowane i projektowe danych syntetycznych

Coordinate component		Initial position	Velocity	Seasonal motion				Offset at 2022.5
				Annual term		Semi-annual term		
		a (m)	b (m/năm)	c (m)	d (m)	e (m)	f (m)	g (m)
North	Designed	-0.0100	0.0200	-0.0010	0.0010	-0.0020	-0.0020	0.2000
	Adjusted	-0.0100	0.0201	-0.0010	0.0010	-0.0021	-0.0020	0.2000
	Deviation	0	-0.0001	0	0	0.0001	0	0
East	Designed	0.0100	0.0100	-0.0200	-0.0050	0.0050	-0.0050	0.2000
	Adjusted	0.0101	0.0100	-0.0200	-0.0049	0.0050	-0.0050	0.1999
	Deviation	-0.0001	0		-0.0001	0	0	0.0001
Up	Designed	-0.0010	0.0200	0.0100	0.0100	0.0100	0.0010	0.2000
	Adjusted	-0.0010	0.0200	0.0100	0.0101	0.0100	0.0010	0.1999
	Deviation	0	0	0	-0.0001	-0	0	0.0001

window containing the offset. It is evident that this anomaly value is substantial (24.1mm), significantly exceeding the threshold value (horizontal dashed green line).

Offset detection in sliding-windows:

After identifying the window containing an offset based on anomalous RMS values, offsets within this window are determined based on the deviation between consecutive coordinates. Specifically, the absolute differences between consecutive coordinates within the window are computed. For a window of 7 coordinates, this results in 6 deviation values calculated as per Formula (3).

$$diff = [|x_2 - x_1|, |x_3 - x_2|, \dots, |x_7 - x_6|] \tag{3}$$

Offset in the window occurs at the deviation with a value greater than 3 times the median of deviations within the window (3.med(diff)).

Figure 3 illustrates the determination of offsets within a window with anomalous RMS values. On the left side of Figure 2, there is a series of 7 consecutive coordinates (blue dots) with an offset at the 4th coordinate. On the right side, there is a series of 6 deviation values calculated from these 7 consecutive coordinates (red dots). It is evident that, corresponding to the offset at the 4th coordinate, the deviation value at the 3rd position is anomalous, significantly exceeding the 3.med(diff). Thus, within the window corresponding to anomalous RMS, an offset occurs at coordinate i if $diff_{i-1} \leq 3$. med(diff).

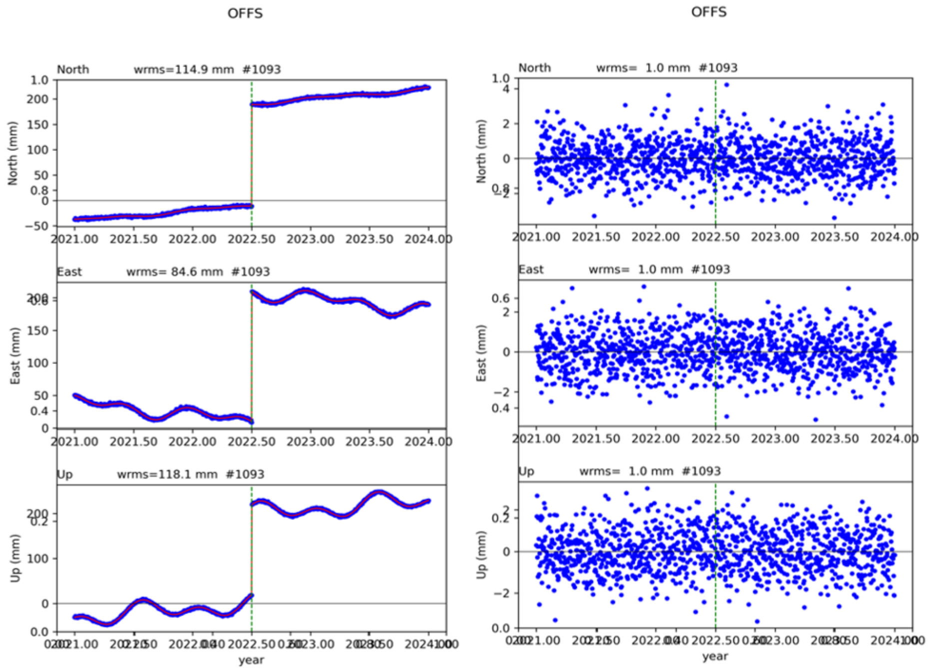
The process of detecting offsets using the above method is accurate, fast, and automated as it can be programmed. The steps outlined above are summarized in the flowchart depicted in Figure 4.

This method of offset detection has been implemented as a module to automatically detect offsets in the GNSS coordinate time series analyzing program 'pygps_ts' using the Python programming language [24], which will be presented in Section 2.3.

2.2. Synthetic model of GNSS position time series and estimation of parameters of synthetic model

The GNSS position time series represents the spatial coordinates of a GNSS station over time within a three-dimensional coordinate system [25]. This time series is visually presented using mathematical equations to analyze the factors contributing to the displacements of observation stations. The predominant mathematical equation, or synthetic model, encompasses parameters that characterize these displacements, specifically: (1) the initial position of the series, (2) tectonic displacement, indicating the movement of the Earth's crust over time (velocity), (3) seasonal motion, which captures displacements based on seasonal patterns, and (4) steps. The GNSS position time series is mathematically modeled using equations for each coordinate component (North, East, Up), as delineated in Equation (4) [26]:

$$y(t_i) = a + bt_i + csin(2\pi t_i) + dcos(2\pi t_i) + esin(4\pi t_i) + fcos(4\pi t_i) + \sum_{j=1}^{n_g} g_j H(t_i - T_j) + v_i \tag{4}$$



a) Measurement and predicted position time series
a) Pomierzone i przewidywane szeregi czasowe

b) Resdual position time series
b) Szeregi czasowe residuów pozycji

Fig. 6. Position time series of OFFS station
Rys. 6. Szereg czasowy pozycji stacji OFFS

where t_i represents the time of the coordinate y (referred to as measurement coordinate), t_i=1,2,3,…,n; a denotes the initial position; b indicates the displacement velocity; c, d, e, and f are parameters of seasonal motion (c and d are of annual term, e and f are of semi-annual term); g_j represents the magnitude of the offset at epoch T_j (n_g is the number of offsets in the series); $H(t_i-T_j)$ is the Heaviside function, $H(t_i-T_j)=0=0$ if $t_i \leq T_j$ and $H(t_i-T_j)=1$ if $t_i \leq T_j$; v_i represents the error term.

Assuming that the epochs T_j of the offsets are known, Equation (4) contains parameters representing the displacements of the GNSS observation stations as unknowns

$$x = [a\ b\ c\ d\ e\ f\ g_1\ g_2\ \dots\ g_{n_g}]^T \tag{5}$$

it is expressed in matrix form as Equation (6)

$$y = Ax + v \tag{6}$$

in which: A is the design matrix, v is the residual vector, and y is the coordinate vector.

Equation (6) is adjusted by least squares. Neglecting the noise, the unknowns is determined by formula (7):

$$x = (A^T A)^{-1}(A^T y) \tag{7}$$

The predicted coordinates are calculated using formula (8):

$$\tilde{y} = Ax \tag{8}$$

The residuals, calculated using formula (9), represent the differences between the measurement coordinates and the predicted coordinates, thus indicating the best fit of the adjusted model.

$$v = y - \tilde{y} \tag{9}$$

Therefore, utilizing a synthetic model to depict the GNSS position time series enables us to estimate the parameters describing station displacement. A pivotal input parameter required for GNSS position time series featuring offsets is the epochs of these offsets. The method proposed for offset detection base on the RMS sliding-window approach as outlined in Section 2.1.

2.3. Development of an automated program for detection of offsets in GNSS coordinate time series

In order to analyze GNSS position time series automatically and accurately, we have developed a program in Python named pygps_ts. This program can automatically detect the epochs of offsets using the method we introduced above, and calculate the displacement parameters of the series. The program's algorithm flowchart is shown in Figure 5.

The steps for processing the position time series of pygps_ts include:

1. Reading the position time series data: The input data is a file containing the GNSS position time series in the format used by the GAMIT/GLOBK [27], which includes information on time and GNSS coordinate values over time.

2. Detecting offsets: Use the RMS sliding-window method to identify and determine the epochs of offsets in the position time series.

3. Formulating and solving the system of equations for each coordinate component of the position time series: Formulate the system of equations for each coordinate component using the determined epochs of offsets using Equation (4). Solve this system of equations using the least squares method to determine the unknowns, which are the displace-

Tab. 2. Adjusted displacement parameters of BD61 and BTIN

Tab. 2. Skorygowano parametry przemieszczenia stacji BD61 i BTIN

Displacement parameters		BD61			BTIN		
		North	East	Up	North	East	Up
Velocity (m/year)		-0.0104	0.0229	-0.0352	-0.0054	0.0424	0.0020
Seasonal motion (m)	Annual term	-0.0007	0.0012	-0.0004	-0.0009	-0.00004	0.0009
		0.0002	-0.0003	-0.0062	0.0008	0.0016	0.0006
	Semi-annual term	-0.0012	-0.0003	0.0010	0.0007	-0.0008	0.0007
		-0.0005	0.0015	-0.0020	-0.0001	0.0003	0.0006
Amplitude of offsets (m)	at 2020.0025	-0.0020	0.0115	0.0017	-	-	-
	at 2020.4540	-	-	-	-48.0265	-223.431	0.0023
	at 2020.8720	0.0031	0.0012	0.0267	-	-	-

ment parameters of the position time series (displacement velocity, seasonal motion, and offset amplitude).

4. Calculating the residual and predicted position time series: Calculate the predicted coordinate series using Equation (8) and the residuals using Equation (9).

5. Printing result: The output comprises the adjusted displacement parameters (displacement velocity, seasonal motion, and offset amplitude), along with the residual time series and predicted coordinates. The adjusted displacement parameters are saved in *.txt format, while the residual time series and predicted coordinates are saved in GAMIT/GLOBK format.

The program pygps_ts has been utilized as a complementary tool in various studies [7, 12, 22]. The entire source code of this program is now freely available via the link DOI 10.17605/OSF.IO/N7V4C.

3. Data, results, and discussion

To evaluate the accuracy and efficacy of the offset detection method and the developed program, two datasets were employed: synthetic data and real data. The synthetic data is a synthetic GNSS coordinate time series model deliberately designed with a predefined offset. Meanwhile, the real data comprises GNSS coordinate time series from two stations within the CORS network operated by Tường Anh Company, experiencing two offsets due to antenna changes during operation.

3.1. Synthetic data and results analysis

The synthetic GNSS coordinate time series model spans three coordinate components — North, East, and Up — over a three-year period from 2021.0 to 2024.0, for a station named OFFS (Offset). This synthetic model encompasses a linear trend, seasonal movements, and an offset at epoch 2022.5, with specific values detailed in Table 1. Subsequently, the data is perturbed with an error of $\sigma = \pm 1$mm following a normal distribution to generate the "measurement" coordinate time series. The designed GNSS coordinate time series for the OFFS station is plotted as blue dots along the time and coordinate axes in Figure 5.a.

The position time series of station OFFS is automatically analyzed by pygps_ts. The results demonstrate accurate identification of the epoch of the offset at 2022.5, with the parameters of the position time series determined nearly identical to their designed values (Table 1). The maximum deviation between the adjusted parameters and the designed ones is only ±0.0001 on the dataset perturbed by a random error of 1mm, as indicated in Table 1, which is negligible.

The processed coordinate time series of the OFFS station is depicted in Figure 6. In Figure 6.a, the red line represents the predicted coordinate series (fit line), closely aligning with the measurement coordinates. Figure 6.b illustrates the residuals of the measurement coordinate series, displaying a wrms of 1mm across all three coordinate components (North, East, and Up), matching the magnitude of the added error, indicating the accurate determination of the predicted coordinate series, closely resembling the designed values (Table 1). In both figures 6.a and 6.b, the vertical dashed blue line indicates the detected offset in the coordinate time series.

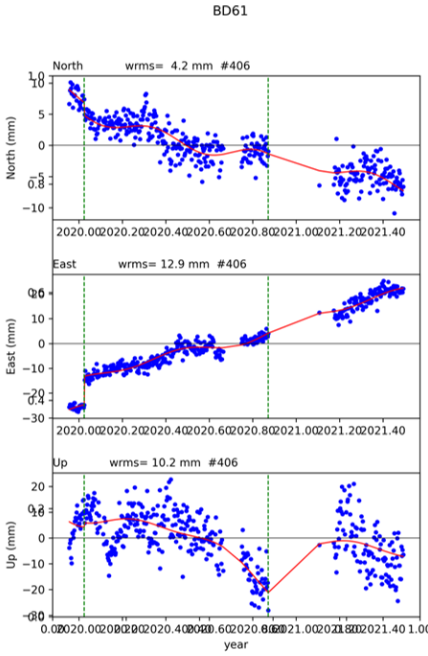
Thus, with the synthetic data, the pygps_ts program accurately identified the epoch of the offset at 2022.5, as designed in the synthetic GNSS coordinate time series. The motion parameters determined closely matched the designed values, with the maximum deviation being only ±0.0001, demonstrating the effectiveness of the method and the program. The wrms of the residual position time series precisely matches the 1 mm noise level, indicating that the predicted coordinate time series was accurately determined.

3.2. Real data and results analysis

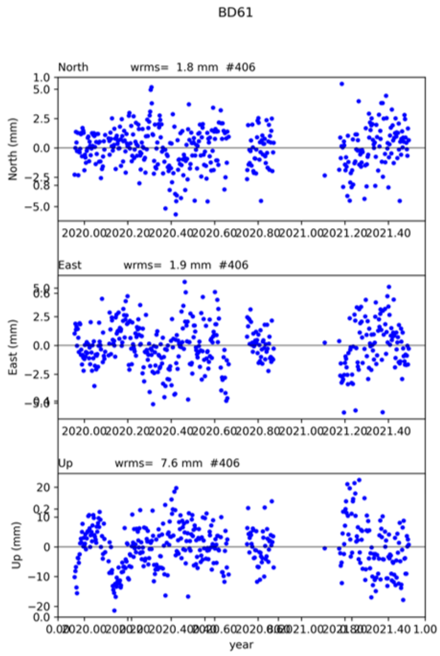
The real data used in the study consists of GNSS coordinate time series from two typical CORS stations within the CORS network, operated by Tuong Anh Science and Technology Equipment Joint Stock Company (TAST) in Vietnam. The TAST network, consisting of nearly 200 stations, is renowned for its stability and accuracy, attributed to the utilization of Trimble's synchronous equipment technology. The selected stations, BD61 and BTIN, were continuously observed for approximately 1.5 years, spanning from 2020.0 to 2021.8. These stations were chosen due to their representation of typical motion patterns observed on the Earth's surface in Vietnam, encompassing linear trends, seasonal movements, and various offsets with differing amplitudes. Specifically, BD61 exhibits two small-amplitude offsets, while BTIN displays a single but large-amplitude offset (refer to Figure 7).

The position time series of BD61 and BTIN were automatically analyzed using the developed program pygps_ts, without any parameter intervention, providing results in less than a minute. The program accurately identified the epochs of the offsets, leading to precise adjustments of the displacement parameters, predicted coordinate time series, and residual coordinate time series of these stations.

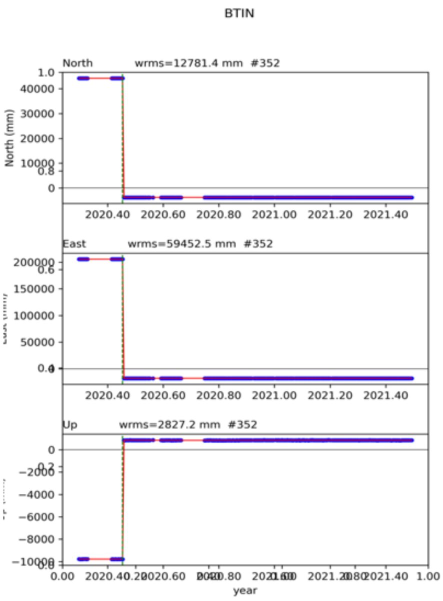
Table 2 presents the adjusted displacement parameters of BD61 and BTIN. showcasing two offsets with relatively small am-



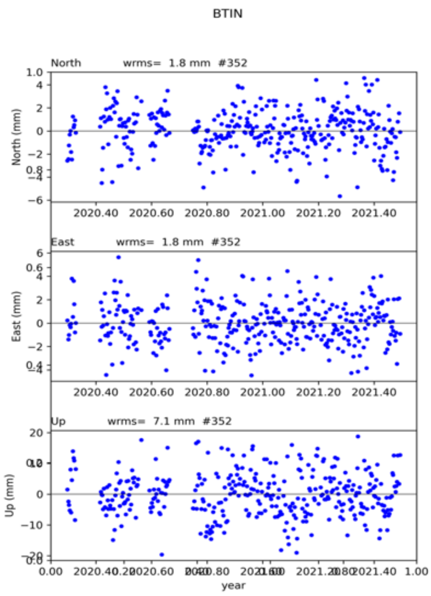
a) Predicted position time series of BD61 station
a) Przewidywany szereg czasowy pozycji stacji BD61



b) Residual position time series of BD61 station
b) Szereg czasowy residuum pozycji stacji BD61



c) Predicted position time series of BTIN station
c) Przewidywany szereg czasowy pozycji stacji



d) Residual position time series of BTIN station
d) Szereg czasowy residuum pozycji stacji

Fig. 7. Position time series of BD61 and BTIN stations
Rys. 7. Szeregi czasowe stacji BD61 and BTIN

plitudes detected in the position time series of BD61, occurring at epochs 2020.0025 and 2020.8720. At epoch 2020.0025, the offset in the East component is 0.0115 m, and at epoch 2020.8720, it is 0.0267 m in the Up component. The amplitudes in the other coordinate components are very small, on the order of millimeters, equivalent to the random noise of the time series.

Conversely, BTIN demonstrates a single offset at epoch 2020.4540, characterized by large amplitudes in the horizontal components, specifically -48.0265 m in the North and -223.431 m in the East, and minimal amplitude, 0.0023 m, in the vertical component (Up).

Figures 7.a and 7.c illustrate the position time series before (blue dots) and after adjustment (red line) for BD61 and BTIN, respectively, while Figures 7.b and 7.d depict the residual coordinate time series (blue dots). Vertical dashed blue lines indicate the identified epochs of offsets. The predicted position time series (red line) accurately calculated from result adjustment, as demonstrated by the residuals closely aligning with the horizontal "0" line. The wrms values are maximal at 1.9 mm for the horizontal components (North, East) and 7.6 mm for the vertical component (Up).

Thus, utilizing real data, the pygps_ts program processed swiftly and accurately. It effectively identified small-amplitude offsets at station BD61 and a large-amplitude offset at station BTIN, showcasing the method and program's flexibility across different scenarios. The wrms value of the adjusted coordinate time series indicates precise reflection of input data and effective handling of offsets.

4. Conclusions

This study presents a novel method for automatic detection and processing of offsets in GNSS position time series, utilizing the RMS sliding-window technique and synthetic models. The developed method was implemented through the pygps_ts program in Python and validated using synthetic and real data.

The program accurately identified the epoch and magnitude of offsets, while processing GNSS coordinate time series quickly and accurately. The results of processing synthetic data showed that the determined displacement parameters matched the designed values. The results of processing real data from two CORS stations in Vietnam, with small-amplitude offsets at station BD61 and large-amplitude offsets at station BTIN, were accurately identified, demonstrating the effectiveness and accuracy of the method and program applied.

The program effectively identified the epoch and magnitude of offsets while ensuring quick and accurate processing of GNSS coordinate time series. Evaluation with synthetic data revealed that the determined displacement parameters closely aligned with the designed values. Similarly, processing real data from two CORS stations in Vietnam successfully identified offsets of varying amplitudes, showcasing the method and program's efficacy and accuracy.

This study contributes a valuable method and tool for GNSS data processing, particularly beneficial in tectonic studies. Given the limited research and early deployment stage of continuous GNSS networks in Vietnam, the presented approach holds significant promise for advancing geodetic studies in the region.

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Conflicts of Interest

The authors declare no conflict of interest.

Literatura – References

1. Amiri-Simkooei, A. R., Hosseini-Asl, M., Asgari, J., & Zangeneh-Nejad, F. (2019). Offset detection in GPS position time series using multivariate analysis. GPS Solutions, 23(1), 1–12. https://doi.org/10.1007/S10291-018-0805-Z/METRICS
2. Bruni, S., Zerbini, S., Raicich, F., Errico, M., & Santi, E. (2014a). Detecting discontinuities in GNSS coordinate time series with STARS: case study, the Bologna and Medicina GPS sites. Journal of Geodesy, 88(12), 1203–1214. https://doi.org/10.1007/S00190-014-0754-4
3. Bruni, S., Zerbini, S., Raicich, F., Errico, M., & Santi, E. (2014b). Detecting discontinuities in GNSS coordinate time series with STARS: case study, the Bologna and Medicina GPS sites. Journal of Geodesy, 88(12), 1203–1214. https://doi.org/10.1007/S00190-014-0754-4/METRICS
4. Cong Duong, C., Yun, H.-S., & Cho, J.-M. (2006). GPS measurements of horizontal deformation across the Lai Chau—Dien Bien (Dien Bien Phu) fault, in Northwest of Vietnam, 2002-2004. Earth, Planets and Space, 58(5), 523–528. https://doi.org/10.1186/BF03351949
5. Cox, A., & Hart, R. B. (2009). Plate tectonics: How it works. John Wiley & Sons.
6. Crocetti, L., Schartner, M., & Soja, B. (2021). Discontinuity Detection in GNSS Station Coordinate Time Series Using Machine Learning. Remote Sensing 2021, Vol. 13, Page 3906, 13(19), 3906. https://doi.org/10.3390/RS13193906
7. Dach, R., & Walser, P. (2015). Bernese GNSS Software Version 5.2.
8. Gazeaux, J., Williams, S., King, M., Bos, M., Dach, R., Deo, M., Moore, A. W., Ostini, L., Petrie, E., Roggero, M., Teferle, F. N., Olivares, G., & Webb, F. H. (2013). Detecting offsets in GPS time series: First results from the detection of offsets in GPS experiment. Journal of Geophysical Research: Solid Earth, 118(5), 2397–2407. https://doi.org/10.1002/JGRB.50152
9. Hazra, A. (2017). Using the confidence interval confidently. Journal of Thoracic Disease, 9(10), 4124–4129. https://doi.org/10.21037/jtd.2017.09.14
10. Herring, T., King, R., & McClusky, S. (2006). GLOBK reference manual—global Kalman filter VLBI and GPS analysis program release 10.3. Massachusetts Institute of Technology.
11. Khazraei, S. M., & Amiri-Simkooei, A. R. (2020). Improving offset detection algorithm of GNSS position time-series using spline function theory. Geophysical Journal International, 224(1), 257–270. https://doi.org/10.1093/GJI/GGAA453
12. Langley, R. B., Teunissen, P. J. G., & Montenbruck, O. (2017). Introduction to GNSS. Springer Handbooks, 3–23. https://doi.org/10.1007/978-3-319-42928-1_1
13. Métivier, L., Collilieux, X., Lercier, D., Altamimi, Z., & Beauducel, F. (2014). Global coseismic deformations, GNSS time series analysis, and earthquake scaling laws. Journal of Geophysical Research: Solid Earth, 119(12), 9095–9109. https://doi.org/10.1002/2014jb011280
14. Montillet, J.-P., & Bos, M. S. (2020). Geodetic Time Series Analysis in Earth Sciences (J.-P. Montillet & M. S. Bos, Eds.; 1st ed.). Springer International Publishing. https://doi.org/10.1007/978-3-030-21718-1
15. Montillet, J.-P., Williams, S. D. P., Koulali, A., & McClusky, S. C. (2015). Estimation of offsets in GPS time-series and application to the detection of earthquake deformation in the far-field. Geophysical Journal International, 200(2), 1207–1221. https://doi.org/10.1093/gji/ggu473
16. Nikolaidis, R. (2002). Observation of geodetic and seismic deformation with the Global Positioning System. University of California, San Diego.
17. Riel, B., Simons, M., Agram, P., & Zhan, Z. (2014). Detecting transient signals in geodetic time series using sparse estimation techniques. Journal of Geophysical Research: Solid Earth, 119(6), 5140–5160. https://doi.org/10.1002/2014JB011077
18. Thomas, H., & Simon, M. (2009, April 4). GAMIT/GLOBK MATLAB TOOLS. Http://Www-Gpsg.Mit.Edu/~tah/GGMatlab/.
19. Tian, Y. (2011). iGPS: IDL tool package for GPS position time series analysis. GPS Solutions, 15(3), 299–303. https://doi.org/10.1007/S10291-011-0219-7/METRICS
20. Tran, D. T. (2013). Analyse rapide et robuste des solutions GPS pour la tectonique [Université de Nice Sophia - Antipolis]. https://www.theses.fr/2013NICE4033
21. Tran, D. T., Nguyen, D. H., Vu, N. Q., & Nguyen, Q. L. (2023). Crustal displacement in Vietnam using CORS data during 2018-2021. Earth Sciences Research Journal, 27(1). https://doi.org/10.15446/esrj.v27n1.102630
22. Tran, D. T., Nguyen, Q. L., & Nguyen, D. H. (2021). General Geometric Model of GNSS Position Time Series for Crustal Deformation Studies – A Case Study of CORS Stations in Vietnam. Inzynieria Mineralna, 1(2). https://doi.org/10.29227/IM-2021-02-16
23. Tran, D. T., Nguyen, T. Y., Duong, C. C., Vy, Q. H., Zuchiewicz, W., Nguyen, Q. C., & Nguyen, V. N. (2013). Recent crustal movements of northern Vietnam from GPS data. Journal of Geodynamics, 69, 5–10. https://doi.org/10.1016/j.jog.2012.02.009

24. Van Rossum, G., & Drake, F. L. (2003). An introduction to Python. Network Theory Ltd. Bristol.
25. Vy Quốc Hải, Trần Đình Tô, & Ngô Văn Liêm. (2011). Determination of present crustal movements of Red River Fault Zone by the TamDao - BaVi GPS network (1994-2007). Vietnam Journal of Earth Sciences, 33(3), 474–479. https://doi.org/10.15625/0866-7187/33/3/438
26. Williams, S. D. P. (2008). CATS: GPS coordinate time series analysis software. GPS Solutions, 12(2), 147–153. https://doi.org/10.1007/s10291-007-0086-4
27. Wu, D., Yan, H., & Yuan, S. (2018). L1 regularization for detecting offsets and trend change points in GNSS time series. GPS Solutions, 22(3), 1–5. https://doi.org/10.1007/S10291-018-0756-4/METRICS

Automatyczne wykrywanie i analiza przesunięć w szeregach czasowych pozycji GNSS przy użyciu metody przesuwanego okna RMS i modelu syntetycznego

W artykule przedstawiono metodę automatycznego wykrywania i analizy przesunięć w szeregach czasowych pozycji GNSS (Globalnego Systemu Nawigacji Satelitarnej) z wykorzystaniem metody przesuwanego okna RMS (Root Mean Square). Technika ta identyfikuje anomalie wskazujące przesunięcia w szeregach czasowych. Aby dokładnie dostosować parametry, takie jak trendy liniowe, sygnały sezonowe i przesunięcia, wykorzystuje się syntetyczny model szeregów czasowych pozycji GNSS. Metoda jest zaimplementowana w zautomatyzowanym programie pygps_ts, napisanym w języku Python. Skuteczność tego podejścia potwierdza się na podstawie zarówno syntetycznych, jak i rzeczywistych danych ze stacji CORS (ciągle działającej stacji referencyjnej) w Wietnamie. Wyniki pokazują, że program może dokładnie i skutecznie wykrywać i analizować przesunięcia, identyfikując epoki i wielkość tych przesunięć w różnych scenariuszach. Niniejsze badanie oferuje praktyczne narzędzie do przetwarzania danych GNSS, które jest szczególnie przydatne w badaniach tektonicznych i zastosowaniach geodezyjnych w Wietnamie, gdzie ciągła sieć GNSS wciąż się rozwija. Badanie pokazuje potencjał tej metody do szerszego zastosowania w monitorowaniu i analizie danych GNSS w różnych regionach. dokładność i skuteczność w wykrywaniu i analizie przesunięć.

Słowa kluczowe: *szeregi czasowe pozycji GNSS, tektonika przemieszczeń, przesunięcie, okno przesuwne, CORS*