Open Geosci. 2015; 7: 140–148 DE GRUYTER OPEN

Research Article Open Access

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Spatio-temporal filtering for determination of common mode error in regional GNSS networks

Abstract: The spatial correlation between different stations for individual components in the regional GNSS networks seems to be significant. The mismodelling in satellite orbits, the Earth orientation parameters (EOP), large-scale atmospheric effects or satellite antenna phase centre corrections can all cause the regionally correlated errors. This kind of GPS time series errors are referred to as common mode errors (CMEs). They are usually estimated with the regional spatial filtering, such as the "stacking". In this paper, we show the stacking approach for the set of ASG-EUPOS permanent stations, assuming that spatial distribution of the CME is uniform over the whole region of Poland (more than 600 km extent). The ASG-EUPOS is a multifunctional precise positioning system based on the reference network designed for Poland. We used a 5-year span time series (2008-2012) of daily solutions in the ITRF2008 from Bernese 5.0 processed by the Military University of Technology EPN Local Analysis Centre (MUT LAC). At the beginning of our analyses concerning spatial dependencies, the correlation coefficients between each pair of the stations in the GNSS network were calculated. This analysis shows that spatio-temporal behaviour of the GPS-derived time series is not purely random, but there is the evident uniform spatial response. In order to quantify the influence of filtering using CME, the norms L_1 and L_2 were determined. The values of these norms were calculated for the North, East and Up components twice: before performing the filtration and after stacking. The observed reduction of the L_1 and L_2 norms was up to 30% depending on the dimension of the network. However, the question how to define an optimal size of CME-analysed subnetwork remains unanswered in this research, due to the fact that our network is not extended enough.

Keywords: GPS, ASG-EUPOS, spatio-temporal filtering, common mode error (CME), stacking

DOI 0.1515/geo-2015-0021
Received April 17, 2014; accepted November 14, 2014

1 Introduction

The vast majority of measurements using the Global Positioning System (GPS) necessitate the existence of thousands of permanently operating stations that form the regional and global networks of reference stations. The ASG-EUPOS (Active Geodetic Network – European Position Determination System) is a multifunctional precise positioning system based on the reference network designed for Poland [1]. At present, approximately 130 reference stations operate together and automatically collect signals from GNSS satellites (GPS and GLONASS). Continuous GNSS measurements are used to precisely estimate the station's positions and their velocities, and also for ionosphere and troposphere studies [2]. The GNSS data is needed to implement the kinematic reference frames in geodesy [3] and interpret changes of dynamic character. The main reason for defining and maintaining of the kinematic reference frames are the continental plate movements. Providing an accurate, stable, homogeneous and maintainable terrestrial reference frame is essential for precise determination of an object's position [4]. The GNSS time series that are obtained in the standard processing contain both signal and noise. The noises in the time domain have already been described by a number of authors, e.g. [5–8] for global or continental networks or [9] for ASG-EUPOS. Besides temporal, the spatial correlation of data for permanent stations located up to several thousand kilometres from each other has also been noticed [10]. The mismodelling of satellite orbits, Earth orientation parameters (EOP), large-scale atmospheric effects, or satellite antenna phase centre corrections, can all cause regionally correlated errors. This kind of GPS

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time series errors are referred to as common mode errors (CMEs) [11–13]. They are usually estimated with regional spatial filtering, such as "stacking". This type of analysis was first used to study the Earth's crustal movements caused by seismic deformations [13], as well as filtering of daily GPS solutions [12]. Stacking was also successfully used to subtract the common mode error [14–16], through analysis of subnets consisting of a limited number of permanent stations (3 to 10). An improvement of continuous daily GPS solutions was shown in [14] by estimating the weighted root-mean-square (WRMS) of raw and filtered residual coordinate time series twice. The successful usage of simple thermoelastic strain model and the local atmospheric temperature to improve the signal-to-noise ratio (SNR) in GPS data was demonstrated in [16]. The aforementioned authors estimated CMEs using weighted stacking formula, but some useful techniques for extracting the CMEs with varying spatial responses can also be applied [11]. These authors indicated three major regional filtering approaches: stacking, principal component analysis (PCA) based on the empirical orthogonal function [17] and the Karhunen-Loeve expansion [18]. They examined five-year data automatically collected on 148 permanent stations incorporated into the Southern California Integrated GPS Network (SCIGN). Nowadays, it is confirmed that common mode errors are not random in networks of up to 500-600 kilometres. The analysis of results leads to the conclusion that stacking could be the optimal method for CMEs subtraction in terms of its low complexity and comparable results to the products of more advanced filtering methods. The main limitation of spatio-temporal filtering is the network size. In the case of a globally distributed set of stations, the baseline distances are generally so large that the stations are considered to be uncorrelated with each other [19]. The question of whether the size of the network affects the accuracy of a station's position and velocity still remains unanswered. Previously published results did not give clearly any relationship between these two issues [20]. The maximum area for which computed CME is of sufficient quality also remains unspecified.

2 Data and regional filtering approach

We used a 5-year span time series (2008-2012) of daily solutions in the ITRF2008 [21] from Bernese 5.0 [22] processed by the Military University of Technology EPN Local Analysis Centre (MUT LAC) [23]. The linear trend and seasonal components (annual and semiannual periodicities widely observed in the analysed time series [24]) were first removed from the XYZ geocentric time series using least squares estimation (LSE). Secondly, the outliers and offsets were removed with median absolute deviation (MAD) [25–27] criterion, assumed to be optimal for GPS-derived coordinates [9] and STARS algorithm (sequential t-test analysis of regime shifts) [28, 29], respectively. Then, the LSE model was restored and the transformation into North-East-Up (NEU) components was completed (in the text we will call this the "raw time series"). The LSE was performed again for NEU components, having subtracted the trend and seasonal changes. The time series obtained in this way will be referred to as the "unfiltered" time series for the rest of the paper. The unfiltered daily time series were characterized by gaps no longer than a few days (and representing no more than 8-10% of data). We assumed that several days gaps (that were present in ASG-EUPOS time series) can be filled in by linear interpolation with no influence on the results. The stacking approach requires us to create an observation matrix, and thus it is necessary to trim the input data to an equal number of epochs. Therefore, the time series have to start and end at the same epoch with the longest common time range possible for all stations. Beyond excluding the time series that were not long enough or that had many gaps from further analyses, we also excluded the ones with strong local effects, as recommended [11]. To meet these requirements, the ASG-EUPOS network was reduced from more than 130 available stations down to 83 with the same time span recorded (Figure 1). The distance between the sub-network barycentre and the farthest permanent station, named GOLE (Goleniow, Poland), is 366 km with more than half of the analysed stations situated no farther than 230 km from the barycentre.

For the set of n permanent stations with time series of m epochs, we construct an $m \times n$ sized matrix $\mathbf{X}$ separately for each of three unfiltered components (N, E, U). The extraction of CME can be applied using non-weighted stacking formula [13] or the weighted approach applied here [12]:

$$\mathrm{CME}(t_i) = \frac{\sum_{j=1}^{n} \frac{X(t_i, j)}{\sigma_{i,j}^2}}{\sum_{j=1}^{n} \frac{1}{\sigma_{i,j}^2}} \tag{1}$$

where: $\mathrm{CME}(t_i)$ is the common mode error value for each of t_i epochs, $X(t_i, j)$ is the i–th row and j–th column element of matrix $\mathbf{X}$, $\sigma_{i,j}$ is the RMS of j–th individual station position in the i–th epoch taken from the least-squares adjustment of GNSS data using Bernese software (as stored in the SINEX files).

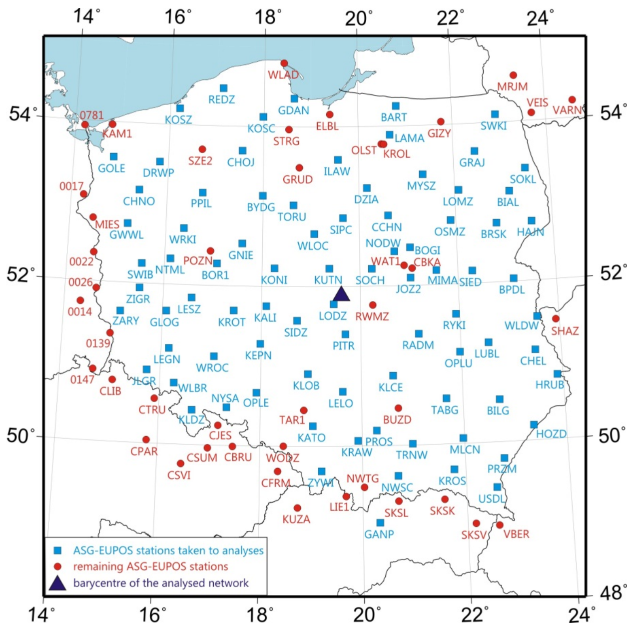

Figure 1: The analysed ASG-EUPOS sub-network consisted of 83 permanent stations distributed all over Poland and one located in Slovakia. The sub-network barycentre is marked with a blue triangle located North-East of the station named LODZ (Lodz, Poland).

Since CME values are assumed to be spatially uniform, the estimated CME value is equal at the corresponding epochs for the analysed component. The computed CME was removed from the unfiltered component value $X(t_i, j)$ by:

$$x(t_i, j) = X(t_i, j) - \mathrm{CME}(t_i), \qquad i = 1, \ldots, m, \ \ j = 1, \ldots, n \tag{2}$$

The filtered component values $x(t_i, j)$ are obtained as the result of the procedure described. The chosen unfiltered and newly formed (stacked) time series are presented in Figure 2 for KUTN station, where the reduction of RMS value was the greatest and quite significant: 7.2% for the North, 6.8% for the East and 13.9% for the Up component. The decrease in the RMS value was also noticed for other stations, but decreased as the distance from the barycentre increased, to only a few percent for stations on the perimeter of the area analysed.

3 The experimental results and analysis

The spatial correlation between different stations for individual components in the regional GNSS networks seems to be significant [11]. One way to measure this correlation is to compute the empirical semivariogram model on the basis of the data points. The distance between data points for which the semivariogram reaches the 95% confidence level is treated as spatial correlation distance. In this research, we computed the correlation coefficient between two selected stations of the sub-network according to the formula:

$$corr\left[X(t, j),\ X(t, k)\right] = \frac{\mathrm{cov}[X(t, j),\ X(t, k)]}{\sigma_{X(t,j)} \cdot \sigma_{X(t,k)}},\ j \neq k \tag{3}$$

where $X(t, j)$ is a chosen component from a single station and $X(t, k)$ is the same component from another station of the network for all of the available epochs. It was noticed here, that the correlation coefficient for the raw time series from two chosen GNSS stations in many cases reaches values higher than 0.95. The causes of high correlation coefficient for the raw time series are largely homogeneous for all regional stations including seasonal terms and linear trends generated by tectonic (Eurasian) plate motion. Besides these obvious correlations, the raw time series also contain some random errors, unmodelled or mismodelled signals, local effects and noise. On the basis of the results presented in Figure 3 for the unfiltered data, the size of station-specific errors in relation to the regionally correlated errors may be estimated. This figure presents the correlation coefficient between each pair in the considered GNSS network.

These correlation coefficients are relatively low for the North and East components. The Up component is characterized by slightly larger correlation coefficient, which reaches values of more than 0.5 for a few of the nearest stations. The low correlation coefficient value can be explained by properly performed time series modelling, resulting in good subtraction of uniform spatial response at all stations. Improvements in estimation of various parameters like tropospheric delays and gradients, orbits and Earth orientation parameters made within the last years is another reason for the small correlation coefficients. It also appears to be important that the correlation coefficient decreases with the increasing distance between stations. This confirms that the common mode error becomes smaller when the sub-network is extended over larger areas. This analysis shows that spatio-temporal behaviour of the GPS-derived time series is not purely random, but that there is evident uniform spatial response, as we assumed at the beginning of this research.

In order to quantify the influence of filtering using CME, the norms L_1 and L_2 were determined. The values of these norms were calculated for the North, East and Up components twice: before performing the filtration and after stacking. These values should represent how the size of the network affects the CME values, and what results in the re-

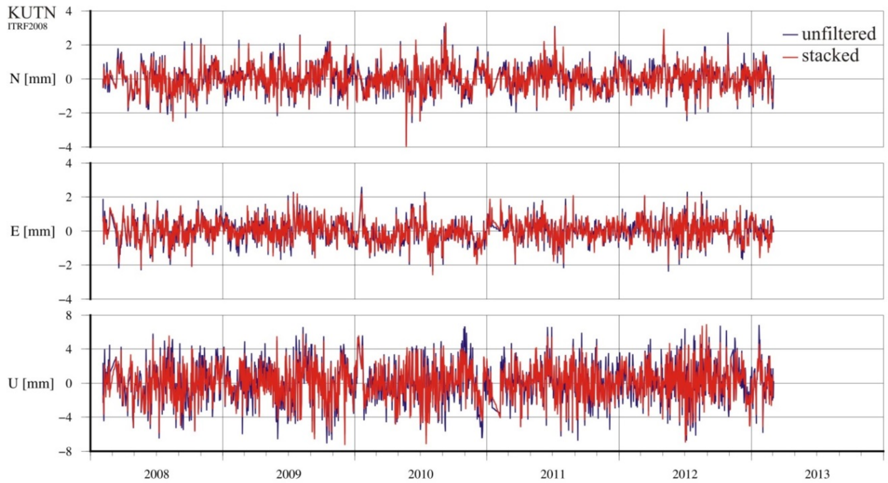

Figure 2: The unfiltered (blue) and stacked (red) time series from KUTN (Kutno, Poland) station.

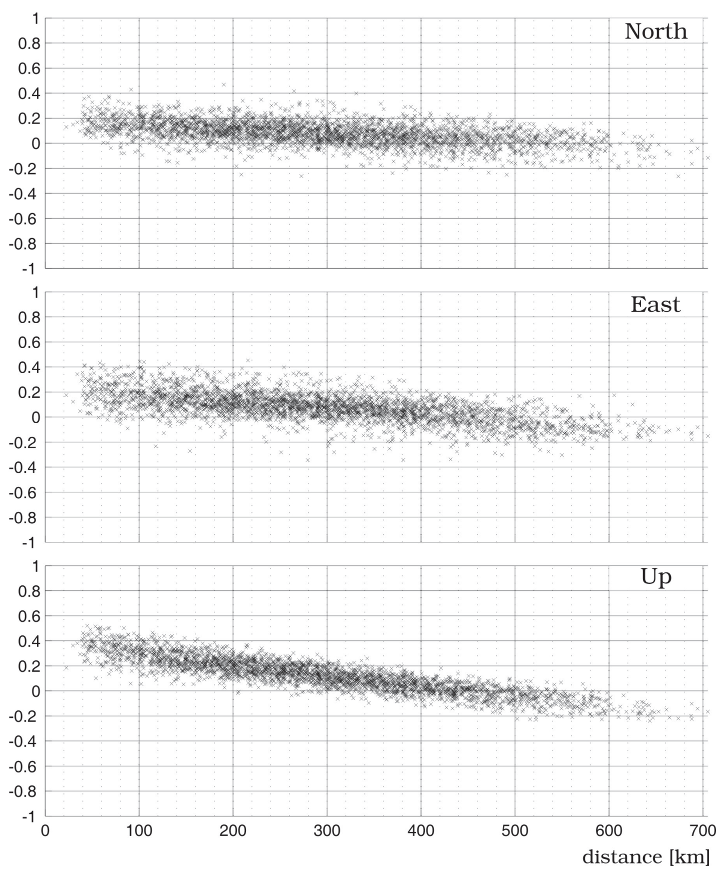

Figure 3: The correlation coefficients for each pair of stations (unfiltered data) in the sub-network in relation to the distance between them.

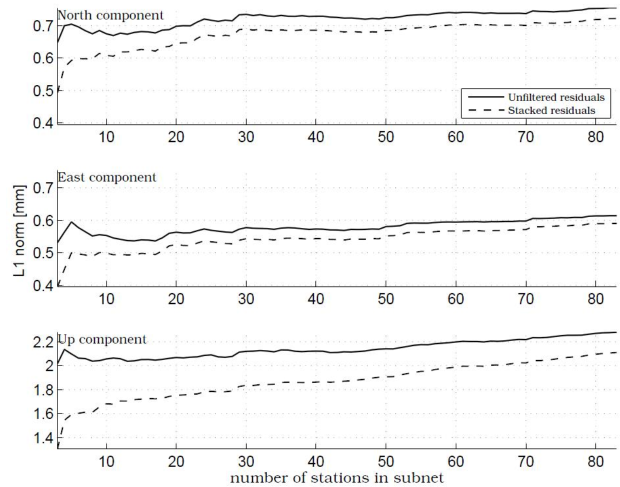

Figure 4: The changes in mean L_1 norm derived from the unfiltered (solid line) and the regionally filtered time series through the stacking approach (dashed line), for several sub-network configurations.

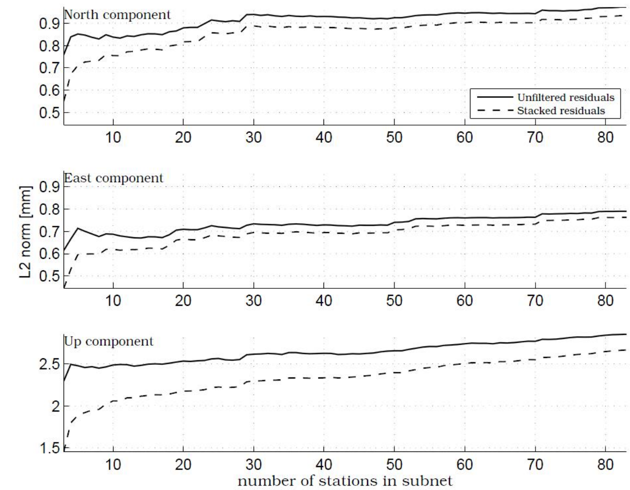

Figure 5: The changes in mean L_2 norm derived from the unfiltered (solid line) and the regionally filtered time series through the stacking approach (dashed line), for several sub-network configurations.

duction of scatter in GPS daily solutions. The L_1 norm computed for the daily sampling interval is defined by the sum of the absolute values of individual components (North, East or Up) divided by the number of stations [11]:

$$L_1(t_i) = \frac{\sum_{j=1}^{n} |X(t_i, j)|}{n} \tag{4}$$

The daily-sampled L_2 norm is the square root of the sum of squared values of individual components divided by the number of stations [11]:

$$L_2(t_i) = \frac{\sum_{j=1}^{n} X(t_i, j)^2}{n} \tag{5}$$

It is important to compare the L_1 and L_2 norms determined using unfiltered and stacked time series. On the basis of this analysis, we can answer the questions about the nature of the CME. One of them is what the optimal value of the CME is, for which the greatest reduction in scatter can be observed. Whether temporal and spatial uniformity in distribution of CME is assumed for ASG-EUPOS permanent stations is also important. The common mode error was computed as the daily weighted mean of the unfiltered data from a set of permanent stations using form (1), and then removed from all stations using form (2). At this stage of the research, we calculated the L_1 and L_2 norms for each of time epochs: first for the sub-network consisting of three stations lying nearest to the barycentre, then in each step we consecutively constructed a new sub-network by adding the next nearest station to the barycentre until obtaining the full 83-permanent station sub-network. Figure 4 and Figure 5 show the comparison of the norms calculated from the unfiltered and stacked data for several sub-network configurations. They present changes of averaged values of L_1 and L_2 norms over the entire range of observation time calculated in relation to the number of stations in the sub-network. They also prove how the removal of CME causes the averages of individual components to decrease – with direct influence on RMS values, even for a set of more than 80 stations.

Figure 4 and Figure 5 show that the proposed application of stacking approach for ASG-EUPOS stations reduces the norms. The enlargement of the network by adding the subsequent permanent stations resulted in slow convergence of mean L_1 and L_2 norms as a function of the size of the constructed sub-network. Table 1 shows how the stacking approach reduces scatter represented by both the mean L_1 and L_2 norms. Each of the columns show how the corresponding norm estimated after stacking decreased for extensive sub-networks.

Based on the analysis presented in Figure 4, Figure 5 and Table 1, it can be concluded that the size of the sub-network plays a significant role in the case of extracting CMEs. The question of how to define an optimal size of CME-analysed sub-network in this research remains unanswered, due to the fact that our network is not extended enough. It is obvious, though, that the selected permanent stations should be representative of the whole network and also should not contain any local effects that can produce poor correlation between two stations. This purely

Table 1: The comparison of the reduction of the mean L_1 and L_2 norms.

Number of stationsin the sub-network [km]	Distance of the fartheststation to the sub-network barycentre	Reduction in norms					
		North		East component		Up	
		L_1 [%]	L_2 [%]	L_1 [%]	L_2 [%]	L_1 [%]	L_2 [%]
5	70	18.8	19.8	19.1	19.7	31.8	31.3
10	103	11.0	11.0	10.9	10.9	22.3	20.7
20	139	8.1	7.6	7.3	6.6	18.0	16.4
30	188	6.5	5.8	6.3	5.5	15.5	13.8
40	220	6.3	5.5	5.5	5.0	13.9	12.4
50	244	5.8	5.1	5.2	4.7	12.2	10.9
60	272	5.4	4.7	4.9	4.5	10.6	9.4
70	305	5.2	4.6	4.6	4.3	9.6	8.5
80	330	4.7	4.2	4.0	3.6	8.3	7.3
83	366	4.6	4.1	4.0	3.5	8.0	7.1

correlated station gets an erroneous CME influence, so that the filtered time series are distorted. The analysed sample of data should be so large that the result of the filtration has to be characterized by the highest precision and reliability possible.

Figure 6 and Figure 7 present the daily changes in the L_1 and L_2 norms determined for the 83-station sub-network. The red dots (stacked residuals) plotted with green lines (unfiltered residuals) show a noticeable reduction in scatter, this indicates the improvement of precision of daily solution time series.

The scatter of L_1 and L_2 norms are larger during summer than winter, despite the removal of annual and semiannual oscillations from the raw time series. This effect can be explained by the temperature-dependent error source in the GPS time series, for example: thermoelastic strain, small-scale atmospheric perturbations and antenna thermal noise. The assumption of spatially uniform distribution of CME is retained only for those regional networks for which the permanent stations recorded more or less similar weather conditions and continental water storage during the whole year. Due to the distribution of ASG-EUPOS permanent stations, which are located in the same climatic conditions, the presence of temporally correlated errors in the position time series is confirmed. Figure 8 presents the reduction of the standard deviation estimated for each component of the 83 ASG-EUPOS permanent stations. They are sorted by the distance to the barycentre of sub-network from the closest to the farthest. A positive value indicates a decrease in the standard deviation. Isolated cases of negative growth prove the existence of some local effects disrupting GPS observations at the station that were unexplained and unnoticed in preliminary analysis.

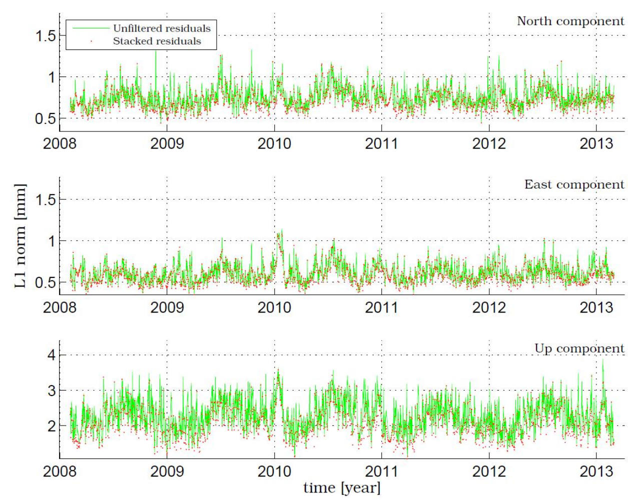

Figure 6: The daily changes of the L_1 norm for the unfiltered (green line) and stacked (red dots) residuals.

In this paper, we demonstrate the application of the stacking approach for 83 ASG-EUPOS permanent stations, assuming that spatial distribution of the CME is uniform over the whole region of Poland (more than 600 km extent). In order to determine the reliability of extracting CME from the North, East and Up components, we calculated the standard deviations of the time series. The lower value of the standard deviation indicates a higher precision of time series (lower scatter). Figure 8 presents that the greatest reduction in scatter was observed for the Up component.

Figure 9 presents histogram plots of standard deviation for the unfiltered and stacked components. The bars slightly

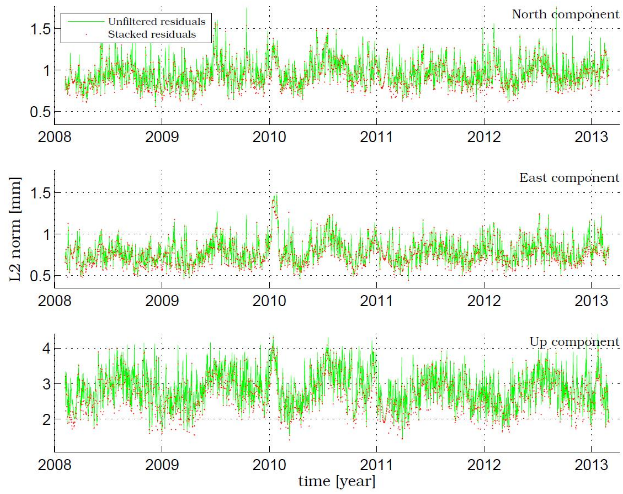

Figure 7: The daily changes of the L_2 norm for the unfiltered (green line) and stacked (red dots) residuals.

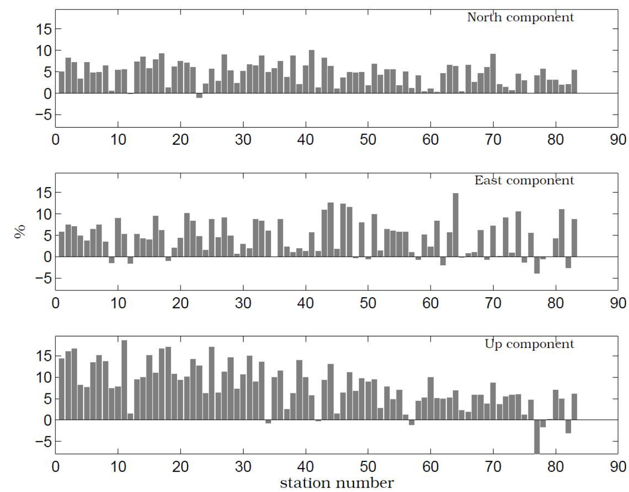

Figure 8: The reduction [%] of the standard deviation through stacking approach.

moved to the left of the graphs demonstrate that in this case the stacking approach caused a reduction in scatter. This improvement also appeared in the mean values of the correlation coefficients between LODZ (station closest to the barycentre of the network) and the remaining stations, which reached 0.007, 0.004 and 0.005 for the North, East and Up filtered components, respectively.

4 Conclusions

The spatial correlations for the time series are quite obvious for the horizontal topocentric components of the GPS permanent stations situated hundreds of kilometres from each other. These correlations for the permanent stations are mainly the result of plate-related trend and seasonal components. The spatial correlation values are greater than 0.9 for the ASG-EUPOS stations, which indicates the existence of almost the same signals for all of the stations. The spatial correlation of the time series residua (referred to as ‘unfiltered’ here) that are obtained after removal of the deterministic part of the time series, in the form of trend and seasonal components, has the value of up to 0.5. This may arise from mismodelling of the satellite orbits, the Earth orientation parameters (EOP), large-scale atmospheric effects or satellite antenna phase centre corrections. On the one hand, the papers published so far have described that the correlation of the ‘unfiltered’ GPS time series can be noticed up to hundreds of kilometres both for global and regional networks [10]. However, the largest area for which the CME value is still homoge-

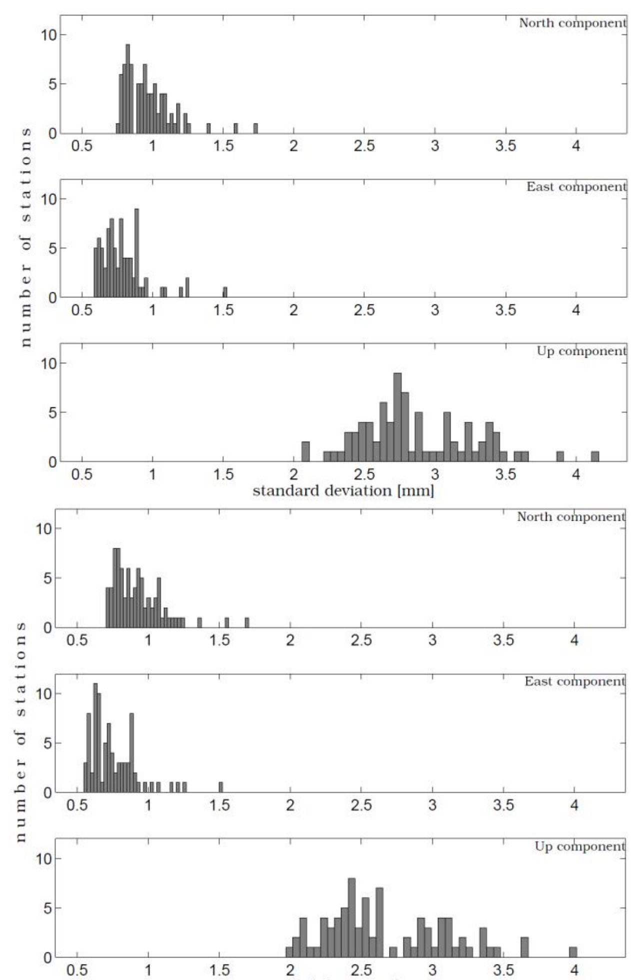

Figure 9: The histograms of standard deviation [mm] for the unfiltered (up) and stacked (down) components.

neous has not been specified yet. In this research, we analysed whether the area of Poland (600 km) may be treated as the one region for the CME estimation. We extended our network starting with its barycentre and adding further stations, widening it from a radius of 70 km to 360 km, and we noticed the deterioration of the L_1 to L_2 ratio from 20 up to 4% and from 30 up to 8% for the values before spatial filtration and after it for the horizontal and vertical components, respectively. This is clear evidence that endlessly widening the network may result in infinitesimal improvement of the ratios, and thus indicates a nearly undetectable CME error. The correlation coefficient was also estimated for the 'stacked' time series that were obtained after spatial filtering. Its values did not exceed the 0.01 that stands for the decrease in the correlation value of 300% in comparison to correlation coefficients before spatial filtering, and practically irrelevant spatial correlation of analysed network. The improvement (decrease) of the correlation coefficient between the ASG-EUPOS permanent stations testifies to the fact that the CME can be treated as homogeneous for the area of Poland. Greater precision and reliability of the spatial filtration results are expected after implementing of the empirical orthogonal functions (EOF) or the Karhunen-Loeve expansion (KLE), which we plan to apply in the near future.

Acknowledgement: This research was financed by the Faculty of Civil Engineering and Geodesy of the MUT statutory research funds. Map was drawn in the Generic Mapping Tool [30].

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