CIVIL AND ENVIRONMENTAL ENGINEERING REPORTS

No. 1 2005

GPS-RTK SIGNAL ANALYSIS CONCEPTION IN APPLICATION TO MONITORING OF ENGINEERING STRUCTURES

Józef GIL
University of Zielona Góra, prof. Z. Szafrana St. 2,
65-516 Zielona Góra, Poland

The paper presents a concept for analysis of GPS-RTK (*Real Time Kinematic*) observations in the aspect of monitoring engineering objects, exposed to deformation. It describes the on-line adaptation algorithm for the blind separation of two statistically independent signals, representing changes of the modules of "zero" vector.
In order to isolate particular oscillations (trend, periodicity) from the signals observed, the exponential equalization of signals was carried out by means of the algorithm of exponential average weights, then the counter-propagation algorithm was used, which, as a vector classifier, eliminated rudimentary noise and disturbances. On that basis it was estimated that GPS signals are inharmonious cyclic signals whose basic harmonious components estimated determine the fundamental changes of the modules of the "zero" vectors.

Keywords: signal analysis GPS-RTK, neural networks

1. INTRODUCTION

Modern GPS technologies broaden the range of the use of methods for solving problems in the field of geodesy. Dynamic measurements effected in a continuous way by means of satellite technology in real time (*Real Time Kinematic*) make it possible to determine the dynamism of deformation changes in engineering objects caused by random factors with changing intensity. According to [4], dynamic measurements are important for determining the phenomenon of the interaction between the foundations of a structure and the ground, they can also be basis for determining permanent displacements and cyclic deformations

ISBN 83-89712-71-7

caused by wind, ice, water (dams, artificial water reservoirs) as well as those caused by thermal and seismic forces. The use of GPS-RTK technology makes it possible to effect measurements which are difficult to achieve by means of classic methods. Monitoring movement of engineering object or changes in the natural environment by means of satellite technology [10] requires the analysis of GPS signals, which can be the basis for verifying the project assumptions adopted or solutions suggested.
The article presents suggestions for the use of neural networks for analyzing GPS signals as changes of the modules of the vectors between the base station and the "moving" receivers, observed by means of RTK technology [9]. The results presented refer to the changes of the modules, analysed within a limited time interval (the number of module changes analysed is only 520).

2. SEPARATION OF SIGNALS AND ELIMINATION OF NOISES

The signals registered by the computer after the average value has been specified are illustrated by the diagrams in fig. 1a and fig. 1b. They show that the oscillations of the signals are within the limit of $\pm 4\,\mathrm{mm}$.

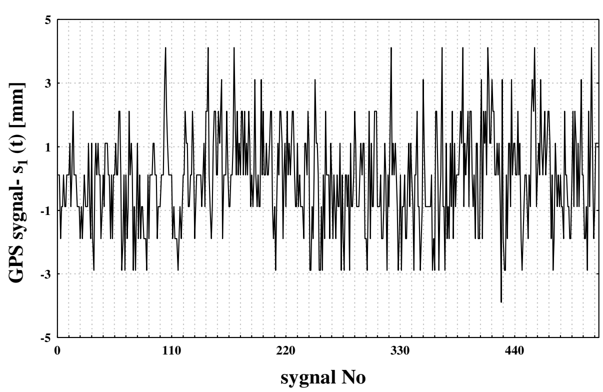

Fig.1a. GPS signal $s_1(t)$

As has been mentioned in the introduction, changes of the modules of two „zero" vectors were observed, which, as has been noted in the article [8], showed small differences in terms of the amplitudes of changes. In order to identify both signals as dynamic objects, i.e. in order to separate them, a linear recurrent network was used according to the suggestion described in the article [1]. Because of the statistical independence of the signals $s_1(t)$ and $s_2(t)$ (the correlation coefficient $r \approx 0$) and nonpredetermined values of the blending matrix (cf. [8]) the method of the adaptive choice of weights was used, which will make it possible to solve the separation problem.

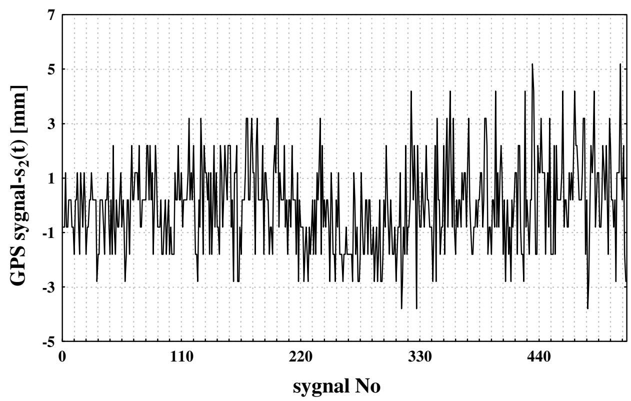

Fig. 1b. GPS signal - $s_2(t)$

When the weight matrix is denoted as

$$\boldsymbol{W} = \begin{bmatrix} w_{11} & w_{12} \\ w_{21} & w_{22} \end{bmatrix}, \tag{1}$$

and bearing in mind the original solution of the separation of signals [5], which disregards feedback, the output signal generated by each of the two neurons is described by the dependence:

$$z_i(t) = s_i(t) - \sum_{j=1, j \neq i}^{2} w_{ij} z_j(t) \qquad (i = 1,2) \tag{2}$$

Hens we will write:

$$\begin{aligned} z_1(t) &= s_1(t) - w_{12} z_2(t) = s_1(t) - w_{12}[z_2(t) - w_{21} z_1(t)] = \\ &= s_1(t) - w_{12} z_2(t) + w_{12} w_{21} z_1(t) \end{aligned} \tag{3}$$

so

$$z_1(t) = \frac{s_1(t) - w_{12} z_2(t)}{1 - w_{12} w_{21}} \tag{4}$$

and similarly

$$z_2(t) = \frac{s_2 - w_{21} z_1(t)}{1 - w_{12} w_{21}} \tag{5}$$

The weight adaptation rule in terms of the matrix has the form [8]:

$$\frac{d\mathbf{W}}{dt} = \eta(t)[f(z(t))[g(z(t))]^{\mathrm{T}} - \mathbf{1}] \tag{6}$$

where one of the functions $f(z(t))$ and $g(z(t))$ is a concave function and the other is a convex function (the form of the function can be different), and $\eta(t)$ is the learning coefficient, which decreases exponentially while the number of iterations increases.

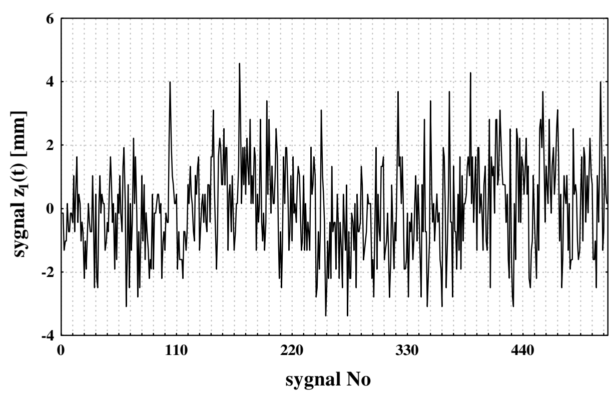

Fig. 2a. The result of the separation – the signal identified $z_1(t)$

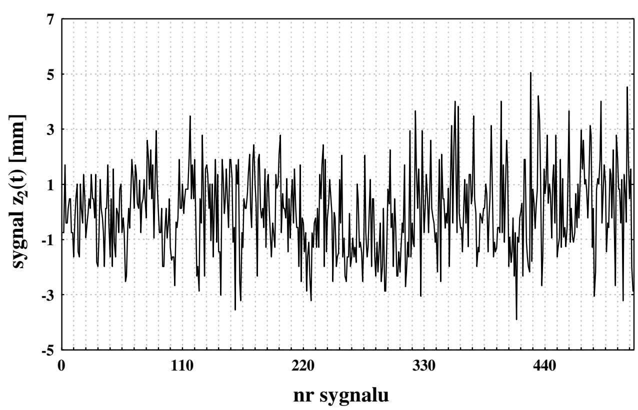

Fig.2b. The result of the separation – the signal identified $z_2(t)$

During the realization of the algorithm typical non-linear functions were used: $f_i(z_i(t)) = z_i^2\ sgn(z_i)$, $g_i(z_i(t)) = arctg(z_i)$ for $i = 1,2$. The iterative process is convergent if

$$\frac{d\mathbf{W}}{dt} = 0 \tag{7}$$

The condition (7) imposes the statistical independence of the output signals z_i and z_j which is ensured by the uneven functions $f(z_i(t))$ and $g(z_i(t))$ introduced into the algorithm, which also add statistical moments of higher levels [7] to the separation process. The stabilization time for the system depends on the choice of the coefficient η (the problem has been solved for the initial value $\eta = 2000$). After balance was achieved the weights had the values:

$$w_{11} = 1 \qquad w_{12} = -0{,}3347739$$
$$w_{21} = +\ 0{,}3927216 \qquad w_{22} = 1$$

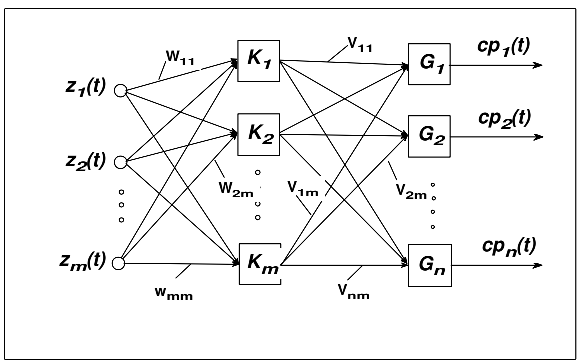

Fig. 3. The structure of a network with counter-propagation

The solution to the problem of separating the signals $z_1(t)$ i $z_2(t)$ has been presented in fig. 2a and fig. 2b. It can be noticed that the character of the changes of the signals separated in comparison to the signals registered is similar but not identical and that the actual signals have cyclic features.

Because of the natural noises of a pair of instruments caused by the instability of the quartz oscillators of the receivers, vector processing of the signals identified $z_1(t)$ and $z_2(t)$ via counter-propagation was used, which generates correct noiseless vectors. Fig.3 presents a simplified structure of a one-direction Hecht-Nielsen neuron network with counter-propagation [3].

Opposite counter-propagation networks have the ability to associate the input vector with the prototype suitable for that vector, but they are also used for function approximation and interpolation as well as data compression [2]. The network is built of two layers: the Kohonen layer and the Grossberg layer, and the number of neurons in particular layers can be different. The Kohonen layer operates in WTA (*Winner Takes All*) mode, and generates the weighed sum for each input signal identified $(z_1(t), z_2(t))$ (current signals) as

$$net_i = \sum_{j=1}^{m} w_{ij} z_j(t) \qquad (i = 1,2,...,m) \tag{8}$$

In the Grossberg layer, which is a layer of linear neurons, the answers $cp_1(t)$ and $cp_2(t)$ are generated as weighed sums of the output signals of the Kohonen layer in the form

$$cp_{1(2)}(t) = \sum_{j=1}^{m} v_{ij} K_j \qquad (i = 1,2,...,n) \tag{9}$$

The symbols in the formulas (8) and (9) are:

net_i - joint stimulation of the i^{th} neuron,
w_{ij} - weights of the neurons in the Kohonen layer,
v_{ij} - weights of the neurons in the Grossberg layer,
K_j - signal of the j^{th} neuron in the Kohonen layer.

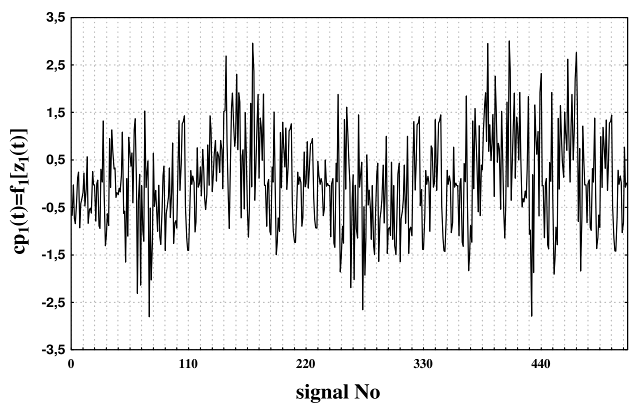

Fig. 4a. The signal $cp_1(t)$ processed via the counter-propagation algorithm

Replicas of the signals processed $z_1(t)$ and $z_2(t)$ via the counter-propagation algorithm in the form of the function $cp_1(t) = f_1(z_1(t))$ and $cp_2(t) = f_2(z_2(t))$ have been shown in fig. 4a and fig. 4b.

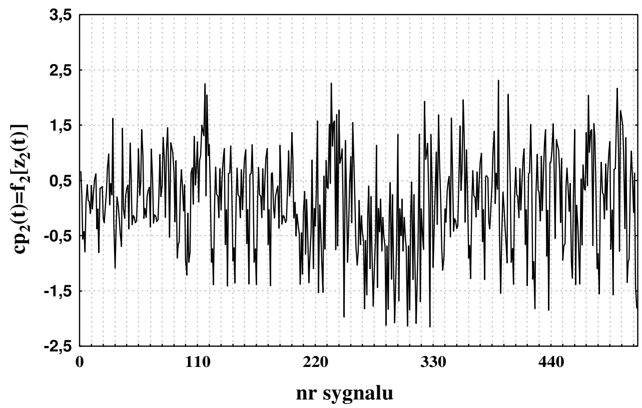

Fig. 4b. The signal $cp_2(t)$ processed via the counter-propagation algorithm

It is possible to notice that the amplitudes of the oscillations of the signals processed via the counter-propagation algorithm decreased considerably in comparison to the amplitudes of the oscillations of the signals after the separation.

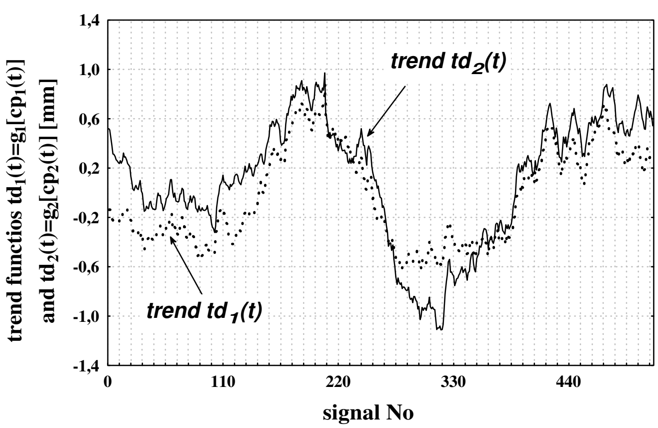

Fig. 5. Trend functions: $td_1(t) = g_1(cp_1(t))$ and $td_2(t) = g_2(cp_2(t))$

Another step of the analysis consisted in formulating the development tendency of the oscillations of the signals $cp_1(t)$ and $cp_2(t)$ in the form of the trend functions $td_1(t) = g_1[(cp_1(t)]$ and $td_2(t) = g_2[cp_2(t)]$. The procedure of exponential equalization is a relatively easy and frequently used procedure for assessing the strength and direction of oscillations. The principle of this equalization consists in smoothing a particular time series with the weighed averages of two realizations of the random variable, i.e. $td(t)$ and $td(t-1)$. The algorithm of the exponential weighed averages is [6]:

$$td(t)_{(exp)} = \varphi td(t) + (1-\varphi)td(t-1)_{(exp)} \qquad (10)$$

where the constant φ considered to be the parameter of rigidity of the exponential equalization is chosen at random from the range (0,1).
It is important to note that an advantage of the counter-propagation algorithm is a short learning time, which is important in the case of time series.

3. PERIODICITY OF THE GPS SIGNAL

After the exponential equalization of the signals processed $td_1(t)$ and $td_2(t)$ it is possible to conclude that the change of the „zero" vector modules recurs periodically, which suggest the possibility of presenting the changes of the signal modules as sums of series of harmonious vibrations (distribution of a periodic function onto the so called Fourier series), which are different in terms of amplitudes, pulsations and initial phases. The Fourier series can be expressed as

$$td_i(t) = \boldsymbol{A_{i1}}\, sin(\omega_{i1} t + \varphi_{i1}) + \ldots + \boldsymbol{A_{in}}\, sin(n\omega_{in} t + \varphi_{in}) + \ldots,\ (i = 1,2) \qquad (10)$$

where:

$A_{\boldsymbol{k}} = \sqrt{a_k^2 + b_k^2}$ - vibrations amplitude,

a_k, b_k - Fourier coefficients of the function determined via the Euler formulas,

ω_k - pulsation,

$arc\, tg\, \varphi_k = \frac{a_k}{b_k}$ - initial phase, for $k = 1,2,\ldots,n)$.

Bearing in mind the above observations in terms of the practical use of the current analysis, three harmonious components of the changes of the periodic inharmonious signals under discussion $td_1(t)$ and $td_2(t)$ were estimated by means of a neuron network. In general, the number of harmonious components of the signals under discussion is large, but in a number of cases of practical use, high frequency components are suppressed.

With a specified number of measurements of actual values of the signals $td_i(t)$ $(i=1,2)$ the objective function $h(\mathbf{x}_i)$ (state function), where $\mathbf{x}_i = [A_{i1}, B_{i1}, \omega_{i1}, \ldots, A_{ik}, B_{ik}, \omega_{ik}]^T$ is defined as [8]:

$$h_i(\mathbf{x}) = \frac{1}{2}[\sum_{j=1}^{k}(A_{ij}\, sin(j\omega_{ij}t) + B_{ij} cos(j\omega_{ij}t) - td_i(t)]^2 \tag{11}$$

As a result of the solution of the three differential equations

$$\frac{dA_{il}}{dt} = -\mu\left[\sum_{j=1}^{k}(A_{ij} sin(j\omega_{ij}t) + B_{ij}\, cos(j\omega_{ij}t)) - td_i(t)\right] sin(l\omega_{ij}t), \tag{12}$$

$$\frac{dB_{il}}{dt} = -\mu\left[\sum_{j=1}^{k}(A_{ij}\, sin(j\omega_{ij}t) + B_{ij}\, cos(j\omega_{ij}t)) - td_i(t)\right] cos(l\omega_{ij}t), \tag{13}$$

$$\frac{d\omega_{il}}{dt} = -\mu_\omega\left[\sum_{j=1}^{k}(A_{ij}\, sin(j\omega_{ij}t) - B_{ij}\, cos(j\omega_{ij}t)) - td_i(t)\right] \times$$

$$\times\left[\sum_{j=1}^{k} jtA_{ij}\, cos(j\omega_{ij}t) - jtB_{ij}\, sin(j\omega_{ij}t)\right] \quad \text{for } l = 1,2,\ldots,k \tag{14}$$

describing how the network works the objective function (11) reaches the minimum value. It results from the form of the formulas (12), (13) and (14) that in this case the network adapts with time to the signal given at the input of the network without the participation of weights. Because of the local minimums in the process the adaptive harmonious estimations, the value of the learning coefficient μ_ω should be considerably lower than the value of the learning coefficient μ. As a result of the numerical realization of the problem, the parameters A_l, B_l, ω_l $(l = 1,2,3)$ of the harmonious components of the functions $h_1(\mathbf{x})$ and $h_2(\mathbf{x})$ reached the values:

- parameters of the function $h_1(\mathbf{x})$ - parameters of the function $h_2(\mathbf{x})$

I. Amplitudes A (mm)

$A_{11} = +\,0{,}49725$ $A_{21} = +0{,}53285$
$A_{12} = +\,0{,}01203$ $A_{22} = +\,0{,}08756$
$A_{13} = -\,0{,}00098$ $A_{23} = +\,0{,}02450$

II. Amplitudes B (mm)

$B_{11} = +\,0{,}00805$ $B_{21} = +\,0{,}09925$
$B_{12} = -\,0{,}00141$ $B_{22} = +\,0{,}02632$
$B_{13} = +\,0{,}00118$ $B_{23} = +\,0{,}02922$

III. Pulsations $\omega\,(\frac{2\pi}{T})$ T - period of one full vibration

$\omega_{11} = -\,0{,}02398$ $\omega_{21} = -\,0{,}02793$
$\omega_{12} = -\,0{,}01818$ $\omega_{22} = +\,0{,}25517$
$\omega_{13} = +\,0{,}33177$ $\omega_{23} = +\,0{,}07020$

Periodical oscillations $h_1(\boldsymbol{x})$ and $h_2(\boldsymbol{x})$ as the sums of three harmonious components have been shown in fig. 6 and fig. 7. The amplitudes specified for the basic components are within the limits of 0,5 mm (approximately), and their pulsations are small in value (0,02-0,03).

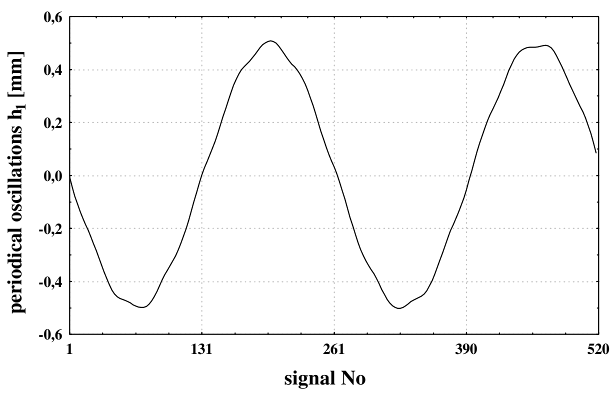

Fig. 6. The periodical oscillations $h_1(\boldsymbol{x})$ as the sum of three harmonious components

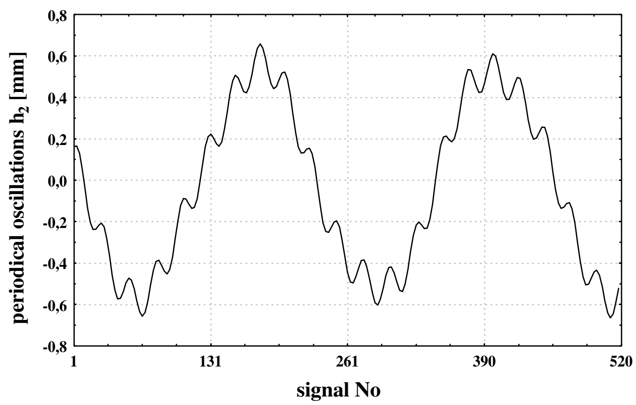

Fig. 7. The periodical oscillations $h_2(\boldsymbol{x})$ as the sum of three harmonious components

The amplitudes of higher harmonious components decrease as their number increases, and the pulsations should be the integral multiples of the pulsation of the basic component. Because of the large number of harmonious components of the GPS signal, the results of the adaptive estimation of the harmonious parameters depend on the values assumed of the coefficients μ and μ_{ω} - especially when the parameter ω is a variable undergoing estimation.

4. CONCLUSION

The method for the analysis of a GPS measurement signal by means of a neuron network can be regarded as one of the ways of effecting GPS-RTK observations, used for examining engineering objects exposed to deformation. A condition for obtaining satisfying monitoring results is a suitable way of eliminating noise in measurement data as time series and a suitable way of decomposing them. In this respect the method of counter-propagation and the algorithm of exponential average weights are noteworthy, which make it possible to obtain a higher level of monitoring resolution. The analysis of the changes of the "zero" vector modules indicates that the character of changes is periodical and inharmonious, consisting of a number of harmonious components where especially important is the basis component whose amplitude value characterizes the accuracy of the location changes of the object under research.

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KONCEPCJA ANALIZY SYGNAŁÓW GPS-RTK W ZASTOSOWANIU DO MONITORINGU OBIEKTÓW INŻYNIERSKICH

S t r e s z c z e n i e

W pracy przedstawiono koncepcję analizy obserwacji GPS-RTK *(Real Time Kinematic)* w aspekcie monitorowania obiektów inżynierskich, narażonych na deformacje. Opisano, działający w trybie on-line algorytm adaptacyjny ślepej separacji dwóch statystycznie niezależnych sygnałów, reprezentujących zmiany modułów wektorów „zerowych”. W celu wyodrębnienia poszczególnych wahań (trendu, okresowości) z obserwowanych sygnałów, dokonano wyrównania wykładniczego sygnałów za pomocą algorytmu wykładniczych średnich ważonych, po czym zastosowano algorytm kontrpropagacji, który działając jako klasyfikator wektorowy eliminował szczątkowe szumy i zniekształcenia. Na tej podstawie ustalono, że sygnały GPS są sygnałami okresowymi nieharmonicznymi, których estymowane podstawowe składowe harmoniczne określają zasadnicze zmiany modułów wektorów „zerowych”.