

GPS interactive time series analysis software

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Abstract Time series analysis is an important part of geodetic and geodynamic studies, especially when continuous GPS observations are used to explore areas with a low rate of deformation. In this domain, having precise and robust tools for processing and analyzing position time series is a prerequisite. To meet this requirement, a new software package called GPS Interactive Time Series Analysis was developed using the MATLAB language. Along with calculating basic statistics and quality parameters such as mean and variance, the software is capable of importing and visualizing different time series formats, determining and removing jumps and outliers, interpolating data, and producing numerical and publication quality graphical outputs. Furthermore, bivariate statistical analysis (such as correlation coefficients, curvilinear and nonlinear regression), residual analysis, and spectral analysis (such as

auto-spectrum, Lomb–Scargle spectrum, evolutionary power spectrum, and wavelet power spectrum) form the main analysis features of the software.

Keywords GPS time series analysis · Jump detection · Regression analysis · Trend analysis · Spectral analysis · MATLAB

Introduction

Continuous GPS observations in the form of time series are often used to monitor crustal deformations. Depending on the nature of the signal and other contributing factors within the time series, various methods are required to distinguish signals originating from the tectonic displacement and the other non-tectonic signals such as seasonal variations. These methods can be used for the following: (1) visual interpretation such as spectrogram, wavelet power spectrum, and recurrence plots (Trauth 2010), (2) time series processing such as convolution and filtering, impulse, and frequency responses of filters, and (3) statistical analysis such as auto-spectral and cross-spectral analysis, interpolation and analysis of unevenly spaced data, evolutionary power spectrum, and wavelet power spectrum.

Several software programs are known to have been specifically developed or published freely and made available for the time series analysis, among them, GAMIT/GLOBK MATLAB[®] (GGMatlab) (Herring 2003), Create and Analyze Time Series (CATS) (Williams 2008), and iGPS (Tian 2011). Despite the good efforts done, more functionalities are still demanded for the time series analysis in Geodesy and Geodynamics studies. For example, tools for data spacing and interpolation, jump detection and removal, and spectral analysis, especially when the data are

The GPS Tool Box is a column dedicated to highlighting algorithms and source code utilized by GPS engineers and scientists. If you have an interesting program or software package you would like to share with our readers, please pass it along; e-mail it to us at gpstoolbox@ngs.noaa.gov. To comment on any of the source code discussed here, or to download source code, visit our website at <http://www.ngs.noaa.gov/gps-toolbox>. This column is edited by Stephen Hilla, National Geodetic Survey, NOAA, Silver Spring, Maryland, and Mike Craymer, Geodetic Survey Division, Natural Resources Canada, Ottawa, Ontario, Canada.

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unevenly spaced, are not available. This becomes crucial for analysis of a large number of time series files with relatively long observation periods, for instance, more than 10 years.

In order to provide a comprehensive, open source, and scientific software for processing and analysis of time series in earth Science studies, the GPS Interactive Time Series Analysis (GITSA) software was recently developed at the Center for Research in Geomatics (CRG), Laval University, using the MATLAB programming language (“[Programming language and the software installation](#)” section). Although the software is basically developed for visualization and analysis of GPS time series in geodetic and geodynamic studies, it can be used for investigating other time series in earth sciences (“[Time series conversion and visualization](#)” section), when the aim of analysis is to investigate the temporal behavior of one of several time-dependent variables within the time series. Examples include the study of long-term record of mountain uplift, sea level fluctuations, millennium-scale variations in the atmosphere-ocean system and so on. In the rest of the paper, we focus on (1) introducing the newly developed software for analysis of GPS time series in general and (2) discussing the new methods and features of the software.

Programming language and the software installation

GITSA was developed using the MATLAB programming language with a Graphical User Interface (GUI). MATLAB provides a high number of tested and ready-to-use algorithms for most data analysis methods and also allows the existing routines to be modified and expanded, or new software to be developed rapidly. In addition, MATLAB is a cross-platform programming language for Windows, Macintosh, and Unix/Linux operating systems. Many applications developed under MATLAB are portable and can be readily run under major operating systems. Moreover, the MATLAB code can be compiled into an executable program, in order to increase the run-time speed.

In order to reduce the computational costs for some algorithms such as Lomb–Scargle or wavelet spectral analysis, GITSA requires the benefit of the MATLAB parallel computing toolbox (PCT). The PCT toolbox provides a maximum of eight MATLAB computational engines to execute applications locally on a multicore desktop. As a direct result, computationally intensive algorithms such as Lomb–Scargle (“[Lomb–Scargle power spectrum](#)” section) or wavelet power spectrum (“[Wavelet power spectrum](#)” section) can be run up to eight times faster by PCT using multicore processors (Sharma and Martin 2008).

Although we tried to develop GITSA independent of operating system (OS), there are still some utility features

such as exporting table data to Microsoft™ Excel® format, or copying figures to clipboard memory, which rely on the OS. Since GITSA has a GUI, in UNIX like OS’s, an X-Window environment should be also installed, and MATLAB should be started with the Java Virtual Machine (JVM) enabled. GITSA also requires the following MATLAB tool boxes: statistics, signal processing and wavelet.

GITSA is freely available as open source software (Weber 2004) under the BSD license (available at www.opensource.org/licenses/bsd-license.php). The source code can be downloaded from <http://sourceforge.net/projects/gitsa>. The GITSA package includes a set of MATLAB m-files (functions), fig-files (GUIs), icons and documents as well as a separate folder for some sample time series files in different formats. To install the software, the downloaded package should be unpacked, and then, the main folder should be added to the MATLAB search path. Additionally, a package called “GUI Layout Toolbox” freely available from MATLAB Central website (at <http://www.mathworks.com/matlabcentral/fileexchange/27758>) needs to be installed as a MATLAB toolbox. After the installation, typing `gitsa` in the MATLAB command prompt will bring up the GITSA main window (Fig. 1).

Features and analysis

The functionality of GITSA covers a broad range from time series data file import and conversion to wavelet spectral analysis. It also comes with some utilities such as a GPS date converter that can convert six different date formats which are often used in GPS applications. However, only the main features of the software are briefly explained here, and more discussion is left for the wiki page of the GITSA software available at <http://sourceforge.net/p/gitsa/wiki/Home/>.

Time series conversion and visualization

GPS position time series are becoming increasingly popular in earth sciences, and many national-scale organizations or research centers publish daily GPS positions in different formats. Despite the popularity, there is no common standard among them. The following list shows the formats supported by GITSA:

- Scripps Institution of Oceanography (SIO) format distributed by Scripps Orbit and Permanent Array Center (SOPAC).
- Plate Boundary Observatory (PBO) format.
- NASA Jet Propulsion Laboratory (JPL) format.
- GAMIT/GLOBK format (Herring et al. 2010).

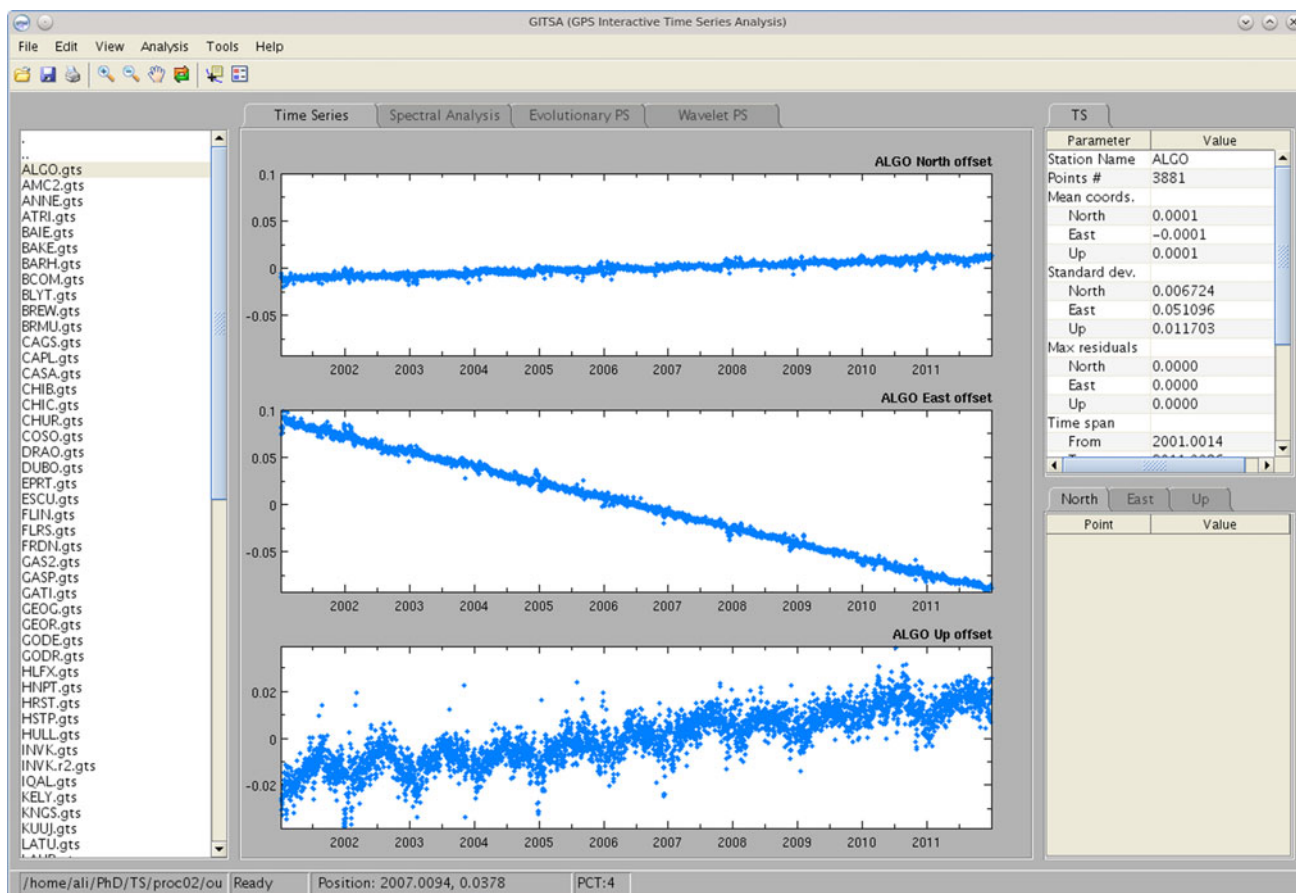


Fig. 1 The GITSA main window showing North, East, and Up components of the ALGO station time series separately (in the drawing area). The left side pane shows the available files in the current directory (the navigation pane). The top right table shows

basic descriptive and statistical information about the time series (the information table). The table below that is reserved to show detected jumps in the time series (the jump table)

GITSA can read and process time series only in its native format (GITSA Time Series format, or GTS). It is an ASCII text format, in which the time series data are stored in 15 space-separated columns including decimal year, year, day-of-year, North, East, and Up coordinates, associated errors to the coordinates (sigma), the corresponding jumps size in coordinates, and the coordinates outlier tags. Lines starting with # are considered as comment and are skipped.

Despite the limitation in reading only the GTS format, GITSA comes with a converter tool to convert these standard formats to each other or to the GTS format. An option called “Arbitrary format” was also implemented in this tool for reading non-standard formats. Using this option, time series in almost any other format can be read. To do this, the user should just determine the corresponding column number of time, coordinates, and the associated errors in the input file.

After having time series files in the GTS format, they can be displayed simply by double clicking on the time series file in the navigation pane (Fig. 1). The North, East,

and Up components of the selected time series are then shown in the corresponding drawing area. It is worth mentioning that all the important plot features such as symbol, color, and thickness can be customized through a preferences file. Following that, the descriptive and statistical information about the time series such as name, mean, standard deviation, maximum residual and so on is shown in the information table.

There are a couple of tools in the toolbar to ease the data visualization, such as Zoom In, Zoom Out, Pan, and Redraw. Inheriting from MATLAB standard toolbar, zooming tools have free and constrained horizontal and vertical options. The pan tool can slide time series freely or constrained to horizontal or vertical directions. Right clicking on the drawing area provides some more visual features such as drawing vertical and horizontal lines, showing dotted lines parallel to time and coordinate axes, or synchronizing time and coordinate limits of the drawing areas. The current position of the mouse pointer over the current drawing area is shown in the status bar of the main window. This is especially useful to highlight a

problematic point such as an outlier in the time series. There is a more advanced alternative for this feature in the toolbar called “Data Cursor”. This tool can give more information about the selected point using “Update Functions”. These functions can be developed by users according to their own needs.

Jump detection and removal

In the GPS time series, jumps or discontinuities in position can be caused mainly by a change in the antenna reference point (ARP) value at the processing time, while other reasons such as tectonic jerk have a secondary level of contribution. The detection of jumps in the time series is a challenging problem either visually or by mathematical methods. The former needs considerable experience and judgment and is therefore subjective, but has the advantage of providing inside details into the device or the station behavior. The latter is more impartial and consistent and can be implemented in the form of a computer code.

Two methods for jump detection, namely “block averaging” (BLKAVG) and “sequential averaging” (SEQAVG), are known from the work of Riley (2008). The emphasis of these algorithms is on detecting jumps in reasonably white frequency residuals after outlier and deterministic drift have been removed from the data. These two algorithms are well explained in Riley’s work, but they are briefed here to give an idea about their performance. The BLKAVG algorithm compares the average values within two non-overlapping moving analysis windows, and declaring a jump if their difference exceeds a certain limit that remains the same through the data set. The SEQAVG algorithm is based on the Rodionov Sequential t Test Analysis of Regime Shifts (STARS) algorithm (Rodionov 2004). It does not use fixed analysis windows, but rather scans the data sequentially. If a suspect point is found that exceeds the jump threshold, the next block of data is examined to confirm or reject the jump. Instead of using a jump threshold based on the Student’s t test, the SEQAVG method uses a fractional frequency jump limit.

These two algorithms as well as our algorithm called “sigma averaging” (SIGAVG) and the “cumulative sum” (CUSUM) algorithm have been implemented in GITSA. The SIGAVG algorithm works in a different way compared to the other approaches. Instead of detecting jumps, it constructs segments without jumps by joining iteratively two statistically compatible segments. This bottom-up algorithm starts by considering all data points as individual segments and stops when there are no longer any consecutive segments which can be joined. The jumps correspond to the border of the segments. This algorithm is still under development. The CUSUM algorithm is well explained by Taylor (2000). It is effective for locating and quantifying

single jumps in otherwise well-behaving frequency data. Interestingly, it is identical to the corresponding normalized (mean-removed) phase data, where a sharp slope change denotes a frequency jump.

Outlier detection and removal

According to Grubbs (1969), an outlier is an observation that considerably deviates from other members of the sample in which it occurs. In all of the existing criteria for testing outliers, the suspicious observation is included in the calculation of the numerical value of a sample statistic, which is then compared with a critical value based on the theory of random sampling to decide whether to keep or to reject the suspicious value. The critical value is the value of the sample criterion which would be exceeded by chance with some specified small probability called “significance level”, based on the assumption that all the observations constitute a random sample.

For detecting outliers in GITSA, a straight line is fitted to the data, and then, errors are estimated. A lower and an upper confidence bounds are computed for the polynomial. Eventually, the data points are evaluated with the confidence bounds, and all the data points that fall out of the bounds are identified as outliers.

Data interpolation

Unevenly spaced data are very common in earth sciences. For example, observations of GPS permanent stations can be subject to malfunctioning of the GPS antenna, receiver, or the communication link with the data center. In this case, interpolation methods become important since spectral analysis methods, such as standard and evolutionary power spectrum, require the interpolated or the evenly spaced data.

Interpolation techniques for $x(t)$ data aims at estimation of x -values for an equally spaced t vector from the irregularly spaced actual measurements (Trauth 2010). There are many methods for interpolation of the unevenly spaced data or time series, such as nearest neighborhood interpolation, linear interpolation, cubic-spline interpolation, and piecewise cubic-Hermite interpolation. However, interpolation methods introduce different types of artifacts. For example, high-frequency components of the signal can be lost in the linear interpolation, or steep gradients in the data sequence can cause false amplitudes in the time series interpolated by the cubic-spline interpolation method. For this reason, it is advised to (1) keep the same number of actual data points before and after the interpolation, (2) explicitly note the interpolation method, and (3) analyze the effect of the interpolation on the variance of the data (Trauth 2010).

GITSA has a tool to examine the data spacing of the time series to see whether it is evenly or unevenly spaced. Then, four interpolation methods including (1) nearest neighborhood, (2) linear, (3) cubic-spline, and (4) piecewise cubic are available. There is also an option to keep number of data points constant. Finally, the standard deviation of the data before and after the interpolation is reported.

Trend analysis

Trend analysis is a method to explore the strength of the relationship between two variables by a single parameter and is usually limited to a rectilinear trend in the bivariate data. The parameter or the “correlation coefficient” is often used in the early stage of a statistical analysis as a preliminary test for linear relationships.

Among different correlation coefficients, GITSA calculates “Pearson’s coefficient”, “Kendall’s tau”, and “Spearman’s rho” as well as their p values for testing the hypothesis of no correlation against the alternative that there is a nonzero correlation. When the p value is small, for example less than 0.05, the correlation value is significantly different from zero. For Pearson’s correlation, p values are computed using a Student’s t distribution for a transformation of the correlation. When the input data is normal, this correlation is exact. For Kendall’s tau and Spearman’s rho, p values are computed using the exact permutation distributions for either small sample sizes or large-sample approximations.

Residual analysis

Small-scale variability in the data can be modeled as follows: data = fit + residual. The residual is analyzed as a new data set to give: residual = new fit + new residual, and so on (Sarma 2009). In other words, the statistics of the residuals gives valuable information about the quality of a model fitted to the data. Residuals have ideally Gaussian distribution with zero mean, that is, they are purely random variables. Based on this fact, the model does not well describe the data when a significant trend is perceived in the residuals. So, in residual analysis, the hypothesis that the residuals have Gaussian distribution is tested using χ^2 test. Because this test is independent of the distribution that is being used, it can be utilized to test the hypothesis that the observations were drawn from a specific theoretical distribution (Trauth 2010).

In GITSA, the current data in the drawing area are assumed to be residuals. Therefore, trends or outliers should be already removed from the time series. The n data points are divided into a number of classes equal to the number of data divided by a constant defined in the

preferences file. Then, classes with frequencies <4 are eliminated. A theoretical or expected frequency distribution is then created with the mean and standard deviation of the residuals. The theoretical distribution is normalized and then scaled to be similar to the distribution of the residuals. After that, both of the distributions are plotted in the corresponding drawing areas. A χ^2 test is performed at a significance level specified by the user, and then, the critical and the calculated χ^2 values are reported.

Regression analysis

Linear regression is the relationship between the response variable y and the input variable x (Ross 2010). Linear models obtained by regression analysis allow the prediction of y value for any given x within the data range (Trauth 2010). Regression analysis allows one to predict the response variable from any arbitrary input variable within the range of the original data value used for the regression analysis. This becomes crucial when one of the two parameters is difficult to measure.

Three widely used regression models in earth sciences, namely (1) reduced major axis (RMA) regression, (2) curvilinear regression, and (3) nonlinear regression, have been implemented in GITSA. There are cases in earth sciences where both x and y variables can be considered independent and therefore subject to error. The RMA regression is one of the common methods used in this case to minimize the distance from both variables in order to compute the best-fitting line. In this method, the area of the triangle constructed by the two perpendicular lines in x and y direction from every data point and the regression line ($0.5 \times \Delta x \times \Delta y$) is minimized (Borradaile 2003). Then, the slope and intercept of the best-fit line are reported along with their standard deviations. The RMA method does not need any input from the user.

The other case, in which values of the input variable are defined or considered to be free of errors, is more common in earth sciences. In this case, the response variable contains errors since its magnitude cannot be determined accurately. The curvilinear regression minimizes the deviations Δy between the response variables of the data points y and the value predicted by the best-fit line/curve y^{pre} , in the least squares sense. In this case, the user has option to choose degree of the polynomial for every component of the time series independently up to 10, and the goodness of fit of one-, two-, or three sigma. Then, coefficients of the best-fit polynomial, as well as the covariance matrix, are reported to the user.

Many bivariate data in earth sciences have a more complicated trend than a linear or curvilinear trend. For example, in a viscoelastic deformation, the strain rises exponentially to a limiting value, or the restoration of the

earth surface after removal of a load (which is accompanied by uplift) is expressed by an exponential relaxation equation (Lowrie 2007). In order to model such cases, GITSA provides some basic nonlinear functions to fit to the data. Users should enter a vector of initial coefficient values. The size of this vector equals the number of parameters of the selected function. A poor set of values of the vector can lead to a poor estimation of parameters, that is, one with large residual error. The user should also define the maximum number of iterations allowed and select the robust fitting option. After all, coefficients of the selected function are estimated as well as the covariance matrix and variance of the errors.

Spectral analysis

Determination of the main frequencies in a time series and finding an explanation of the system from which the measurements were derived are the main objectives of spectral analysis (Shumway and Stoffer 2011). In other words, spectral analysis methods aim to find frequency patterns in the time series. Since real time series in earth sciences are influenced by various phenomena other than the primary signal or have an uneven time space, GITSA provides different methods to detect and measure the cyclic behavior of the time series. These methods are introduced in this section. It should be noticed that time series in earth sciences are often subject to a long-term linear trend. This trend is wrongly interpreted as a signal with a very long period by the spectral analysis methods and produces a large peak with a frequency close to zero in the spectra. As a result, it is recommended to remove the trend of the data (“[Trend analysis](#)” and “[Regression analysis](#)” sections) before the spectral analysis.

Auto-spectral analysis

Auto-spectral analysis describes the distribution of variance incorporated in a single signal as a function of frequency or wavelength. GITSA computes the power spectral density (PSD) of the time series using the periodogram method. This method is a special case of the Blackman and Tukey method (Blackman and Tukey 1959), with the lag parameter equal to unity (Muller and MacDonald 2002). A set of parameters including window vector, length of the Fast Fourier Transformation (FFT), and sampling frequency should be defined by the user when using this method. The window vector defines the coefficients of the window used in computing a modified periodogram of the input time series. The window allows one to overcome the spectral leakage. The window vector should have the same length as the time series. A rectangular window equivalent to the standard periodogram is

used if the user does not define the window vector. Length of the FFT is equal to the larger of 256 and the next power of two greater than the length of the time series. In general, it determines the length of the PSD and the range of the corresponding normalized frequencies. When the length of FFT is longer than the length of the time series, it is padded with zeros. The sampling frequency is specified as an integer in Hertz (Hz) to compute the PSD and the corresponding vector of frequencies.

Eventually, the PSD is plotted in the corresponding drawing area in the “Spectral Analysis” tab, and then, the first three significant peaks equivalent to the first three major signals in the time series are highlighted. The period related to each peak can be determined using the Data Cursor tool in the toolbar or the Annotate tool in the context menu.

Amplitude spectral analysis

The phase shift of the signal cannot be computed in the auto-spectral analysis. In this case, amplitude spectral analysis is applied to calculate the amplitude, frequency, and the phase shift of the signal using the FFT method. Similar to the auto-spectral analysis, the PSD is computed and then scaled by the length of the time series. The PSD is also multiplied by two in order to keep the same energy as in the symmetric spectrum, except for the first data point (Trauth 2010).

This method requires the length of FFT and the sampling frequency to be defined by the user. Same as the auto-spectral analysis, the PSD is plotted in the corresponding drawing area in the “Spectral Analysis” tab (Fig. 2), and then, the first three significant peaks are highlighted. In this method, however, it is possible to draw the cosine curve corresponding to that frequency peak on the time series.

Evolutionary power spectrum

Although the auto-spectral and amplitude spectral analysis reveal the significant frequency patterns in the time series, they do not provide any information about variability in the amplitudes of these peaks through time. Evolutionary power spectrum (EPS) maps changes in frequency patterns through time. In other words, if the amplitude of spectral peaks change with time, this method is able to map it in the frequency domain using the short-time FFT (SFFT). The result of the EPS is the short-term, time-localized frequency content of the signal (Trauth 2010). This method requires evenly spaced data.

To compute the changes in the power spectrogram with time, GITSA requires a set of user-defined parameters such as window vector, overlap size, length of FFT, and sampling frequency. Except for the overlap size, they are

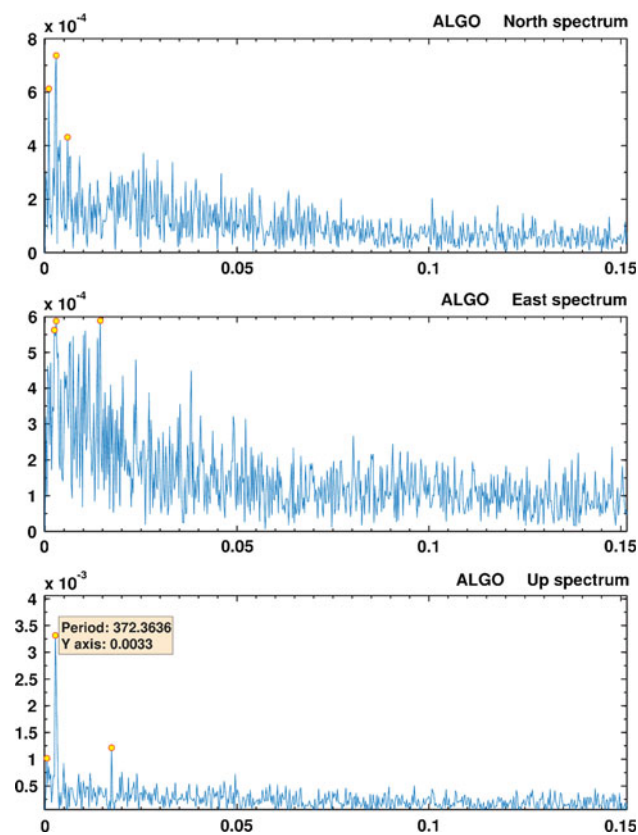


Fig. 2 The power spectral density for ALGO station using the FFT function. The first three significant peaks have been highlighted using *circles*, and the highest frequency peak has been annotated by the context menu tool. It is also possible to add the highlighted peaks to the jump table

similar to inputs of the auto-spectral analysis (“[Auto-spectral analysis](#)” section). By default, the time series is divided into eight segments with 50 % overlap to other segments. Each segment is then windowed with a Hamming window to suppress the spectral leakage. The output of the spectrogram is a colorful plot that displays vertical stripes corresponding to the significant maxima at the major frequencies in time series. The results have a lower accuracy in this algorithm whenever the temporal resolution is higher.

Lomb–Scargle power spectrum

The previous analysis methods of power spectra require evenly spaced data. These types of data are uncommon in earth sciences, and therefore, data interpolation becomes frequently mandatory (“[Data interpolation](#)” section). In this case, an alternative method called “Lomb–Scargle algorithm” can solve the problem (Scargle 1981, 1982, 1989; Press 1992; Schulz and Stattegger 1997). This algorithm evaluates the time series data just at the measured times and does not need any interpolation of the

unevenly spaced data. Furthermore, quantitative significance testing of the results is also possible. Despite its strength, this method has limitations in mapping temporal changes in the frequency domain.

To compute the Lomb–Scargle spectrum, GITSA needs the following parameters to be entered by the user: over-sampling factor, highest frequency, Nyquist frequency, and the test significance level. The over-sampling parameter influences the resolution of the frequency axis. The highest frequency is the maximum frequency that can be analyzed by the Lomb–Scargle algorithm. For choosing the highest frequency, Trauth (2010) recommends to take Nyquist frequency that would be obtained if the data points were evenly spaced over the same time interval.

It is also possible to compute the significance level of the results suggested by Press (1992). In this method, the equation for false-alarm probability of the null hypothesis is inverted to compute the corresponding power of the significance level (Trauth 2010).

Wavelet power spectrum

Wavelet power spectrum is an alternative method for the evolutionary power spectrum to map temporal variations in the spectrum. The wavelet transform uses base functions called “wavelets” which have smooth ends by themselves. Different to the FFT spectra, wavelets can readily map changes in the time–frequency domain because they can be stretched and translated in both frequency and time with a flexible resolution (Trauth 2010). As for the FFT methods, the wavelet transform requires evenly spaced data.

To compute the wavelet power spectrum, GITSA needs the following parameters to be defined by the user: the wave type, scales, and the sampling period. The following wavelet families are supported in GITSA: Haar wavelet, Daubechies wavelets, symlets, coiflets, biorthogonal wavelets, reverse biorthogonal wavelets, Meyer wavelet, discrete approximation of Meyer wavelet, Gaussian wavelets, Mexican hat wavelet, Morlet wavelet, complex Gaussian wavelets, Shannon wavelets, frequency B-Spline wavelets, and complex Morlet wavelets. The scales determine how much a wavelet can be extended or compressed in order to represent the variability of the time series at different wavelengths. Low scale values compress the wavelet and correlate better with high frequencies. Therefore, details with rapid changes can be mapped better with lower scales. High scale values stretch the wavelet and correlate better with the low frequency content of the signal. Consequently, higher scales are more suitable for long-term variations. The sampling period is used to convert the scales to the pseudo-frequencies.

Future developments

GITSA is an active open source software project for implementing different algorithms for GPS time series analysis. In addition to what has been developed so far, there is a list of features that will be implemented in near future. Considering priority, the list comprises (1) filtering methods (including convolution, recursive and non-recursive filtering, common-mode errors filtering, impulse and frequency response, and adaptive filtering) and (2) nonlinear time series analysis including offsets and post-seismic decay modeling. However, as an open source project, other innovative ideas and code development contributions are welcomed.

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Rock Santerre is a full professor of Geodesy and GPS in the Department of Geomatics Sciences and a member of the Center for Research in Geomatics at Laval University. Since 1983, his research activities have been mainly related to high-precision GPS for static and kinematic positioning. Dr. Santerre is the author and coauthor of more than 150 publications, and he holds three patents related to GPS equipment.



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