GPS-structural health monitoring of a long span bridge using neural network adaptive filter

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The movement of bridge deck bearings plays a significant role in the safety of bridges. Real time kinematic global positioning system (GPS) continuous health monitoring using relative deformations was carried out on a long span Zhujiang Huangpu Bridge. The neural network aided adaptive filter is used to predict and adjust the GPS monitoring data. The statistical moments in time and frequency domains were used to analyse the movement of the bridge deck. The results indicate that (1) the proposed neural network with the adaptive filter model can be used to de-noise the GPS health monitoring signals, (2) the GPS is highly sensitive for bridge deck movements, (3) the statistical moments can be used to detect the movements and errors of the GPS observations, and (4) the bridge is very safe under different loads.

Keywords: RTK, GPS, Monitoring, Neural network, Adaptive filter

Introduction

Global positioning system (GPS) is being actively applied to measuring static and dynamic displacement responses of large civil engineering structures under different loads [**30**], [**11**], [**5**], [**4**], [**12**], [**21**]. The measurement principle works worldwide, continuously and under all meteorological conditions, and therefore holds promise as a way to monitor the movement of structures [**15**]. The structural monitoring system is responsible for the reliable collection of response data measured using GPS with/or other sensors installed in the structure. The structural health monitoring (SHM) is a process of measuring the deformation and detection the damage of structures. The goal of SHM is to improve the safety and reliability of aerospace, civil, and mechanical infrastructure by detecting deformation and damage before it reaches a critical state [**7**], [**22**].

Traditional real time kinematic (RTK) GPS positioning adopts single reference station, and was often adversely affected by systematic errors such as ionospheric and tropospheric delay [**30**]. Yeh *et al.* concluded that the rover station must be located within ~10 km of the reference station to achieve centimetre level accuracy [**30**]. Medium range (~50 km) RTK GPS positioning has been proven to be feasible for highly precise applications [**30**]. With the development of RTK GPS receiver and antenna technology, GPS is currently used in areas where high measurement precision is required within high dynamic environment [**11**], [**12**], [**10**], [**24**]. In addition, continuous GPS measurements have been used now nearly 15 years for estimation of crustal deformation [**1**]. On the other hand, Been *et al.* and others summarised the GPS technology in the SHM [**15**], [**2**], [**14**], [**25**], [**8**].

There are numerous sources of errors that affect the GPS measurements. It is known that most of GPS errors were removed with using differential GPS technique except multipath errors. In addition, without the correction available from a dual-frequency measurement the ionosphere can produce the largest of these errors [**3**], [**20**]. Better measures of the magnitude and stability of the errors contributed by the satellites are being sought [**3**]. Likewise, attention is being given to calibrating the multipath errors in receiver systems [**24**]. Accurate correction for these errors is necessary to increase the accuracy in many GPS applications. Herein, most of the continuous RTK GPS health monitoring observation signals (displacement time histories) processed using the company software for the GPS system used. In the other hand, the errors analyses of the estimates of continuous GPS positions have received a lot of attention in the last few years [**11**], [**5**], [**4**]. The signal processing methodology is one of the core issues in GPS errors elimination. An example of a digital signal processing system is the adaptive filter (AF).

An adaptive filtering technique has been used wider and wider since the 1960s [**10**], [**18**], [**23**]. When the priori knowledge of input signal is unknown, the AF can adjust the weight coefficient after N iterations, so as to achieve the best filtering. The minimum mean square error as the standard of traditional AF has the drawback of excessive computing [**23**]. The neural network (NN)'s whole connection among layers is a one-way connection. The

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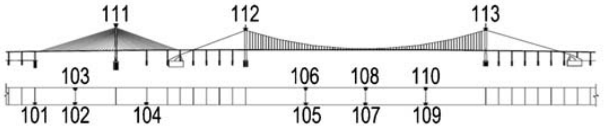


1 GPS health monitoring system on Zhujiang Huangpu Bridge

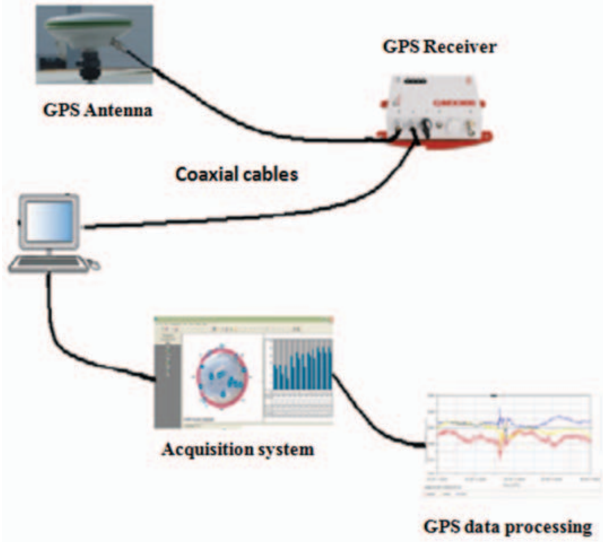
learning process is composed of the input's forward-propagation and errors' back propagation [**28**]. The hidden layer neuron uses sigmoid function. Although the increase in layers can improve the accuracy, but the network also needs more training time. Therefore, this article used the network topology that contains a hidden layer structure. Errors in hidden layer are decreased by increasing the number of neurons [**18**], [**23**], [**28**], [**27**]. The NN and AF are used separately or combined with other filters in the process and identified GPS and monitoring signals before, refer to [**18**], [**29**], [**26**], [**9**].

However, the focus of this research is: (1) to examine the NN with AF in errors elimination of GPS survey observations, (2) to use the linear NN with AF to process the continuous RTK GPS observations, (3) to demonstrate the possibilities that the GPS data processing technique can be used in SHM, and (4) to analyse the deck bridge deformation based on RTK GPS monitoring system.

GPS health monitoring system

The GPS health monitoring system of Zhujiang Huangpu Bridge in China for the case study bridge is discussed in this section. This bridge is composed of a 705 m-long cable-stayed bridge and an 1108 m-long cable-suspended bridge. The width of deck and the height of towers for the Bridge are 34·5 and 195·476 m, respectively. There were 14 GPS units installed on the two bridges after August 15, 2009, including 13 rover stations and 1 base station as shown in Fig. 1.

The distance between base station and point (107) is 1·00 and 1·50 km from point (101) according to Fig. 1. The reference station refreshes the RTK correction messages for the GPS monitoring stations with a frequency of 1 Hz via the optical fibre communication system. LEICA Geo-systems antennas and dual-frequency GPS receivers were used to observe the GPS satellite signals; the satellite elevation cut-off angle is 13°, at least nine satellites. The observations were split into single hour observations for the processing purposes. The data collected were mixed with that generated by the receivers' own oscillators, and then LEICA Spider 2·1 RTK software was used to process RTK GPS data. The data collected are processed coordinates in World Geodetic System (WGS-84) and converted to the local coordinate system by the coordinate transformation, Ogundipe *et al.* [**21**] and Elsheimy [**6**] summarised the coordinate transformation system which was used in this case of study. A local bridge coordinate system was established to be used in the analysis and the evaluation of the observation data. The X data represent the relative displacement changes along the longitudinal direction of the bridge; the Y data represent the relative displacement changes along the transverse direction of the bridge while the Z data represent the relative displacement changes along the altitude direction of the bridge [**11**]. The outputs from GPS monitoring stations include monitoring point number and RTK GPS three-dimensional coordinates, GPS time, satellite status data, GPS receiver status data, and so on, and the raw GPS outputs, if required as shown in Fig. 2. The resonant frequency of the bridge is considered a very important parameter in the bridge structural and safety analyses. The relative displacement changes of the bridge deck will be in millimetres.



2 GPS network scheme

The neural network adaptive filter model

There are many algorithms applied to the AF. For example, least mean square (LMS) algorithm as well as its various improved algorithms, recursive least square algorithm, fast transverse filter algorithm [**23**], etc. The basic objective of an AF model is to set its parameters, in such a way that its output tries to minimise a meaningful objective function involving a reference signal [**18**], [**17**]. Adaptive finite-duration impulse response (FIR) filters are the most popular ones due to their stability [**18**]. The structure of the FIR filter is shown in Fig. 3*a*. Here, we can define the complex-valued tap-weight vector with M coefficients as

$$\hat{\mathrm{w}}(n) = [w_0(n), w_1(n), \ldots, w_{\mathrm{M}-1}(n)]^{\mathrm{T}} \tag{1}$$

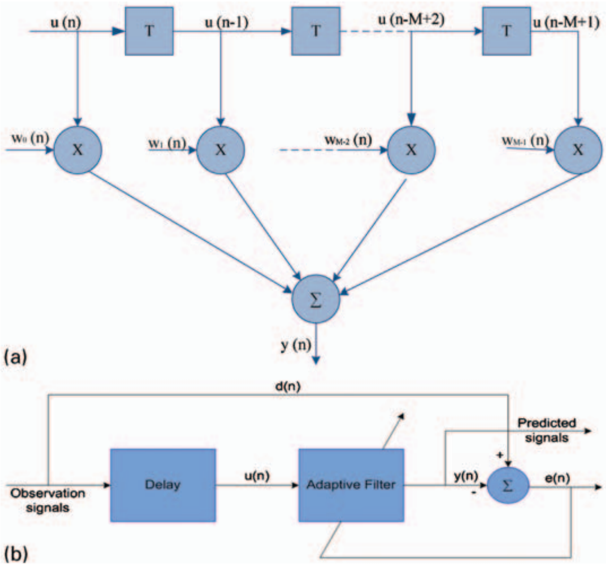
where $[\cdot]^{\mathrm{T}}$ is the transpose of a vector or a matrix. With the M-length tap-weight vector shown as above, the complex-valued input signal can be defined as

$$u(n) = [u(n), u(u-1), \cdots, u(n-M-1)]^{\mathrm{T}} \tag{2}$$

where the $u(n)$ denotes the input signal, then the output of the filter is

$$y(n) = \hat{\mathrm{w}}^{\mathrm{H}}(n)u(n) \tag{3}$$

where $[\cdot]^{\mathrm{H}}$ is the Hermitian transpose of a vector or a matrix and $y(n)$ is the AF output signal. Herein, $d(n)$ is used as a reference or a desired signal at time instant n. Therefore, the error signal $e(n)$ is calculated as $e(n)=d(n)-y(n)$. The error signal is then used to form a performance function that is iteratively minimised by the adaptation algorithm in order to determine the appropriate updating of the filter coefficients. The

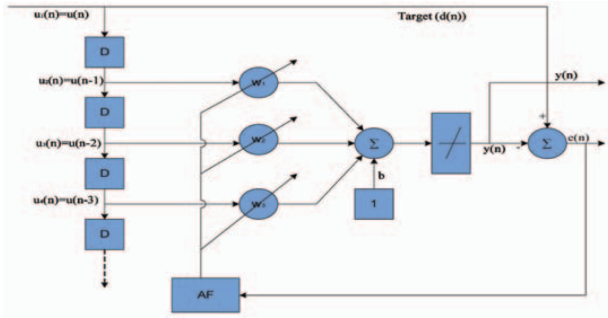


3 ***a*** **FIR filter: time-shifted structure of the input signal and** ***b*** **adaptive filtering prediction model**

minimisation of the objective function implies that the AF output signal matches the desired signal in some sense [**10**], [**28**], [**27**], [**17**]. Meng *et al.* summarised that the AF applications are: system identification in layered, earth modelling, predictive deconvolution in adaptive equalisation, linear predictive coding in signal detection and echo cancellation in adaptive beamforming [**18**]. This study will use the AF to predict the smooth GPS deformation signals as shown in Fig. 3*b*.

The NN is motivated by their ability to approximate an unknown nonlinear input–output mapping through supervised training. The NN has two remarkable properties: it can realise a multi-input and multi-output arbitrary nonlinear mapping by adjusting the link-weights besides NN has the generalisation ability due to its nonlinearity [**9**]. The universal phenomenon for nonlinear system is used to build the precise mathematical NN model. Therefore, these increase the difficulty of real time estimation for the system. It is well known that one of the useful methods for delay time compensation is the predictive technique [**9**].

The NN in this work will be incorporated into the AF in order to compensate the model uncertainties [**18**], [**23**], [**28**], [**27**], [**9**], [**17**]. Herein, the time-delay neural network is a multilayered NN, in which the steepest descent technique is employed to adjust the link weights so that the differences between the NN outputs and the desired outputs are minimised. The idea is to incorporate a linear NN into the AF, and train the NN so that the NN realise a mapping from the measurement to the additive correction to the estimation of the AF. The input vector to the NN is a set of the measurement and the previous corrected estimation. The output vector of the NN is a desired signal additive correction to the AF-estimated state vector to obtain the corrected estimation of the filter weight coefficient, as shown in Fig. 4. This study depends on linear NN aided AF with LMS algorithm. LMS algorithm is based on minimum mean square error criteria, and it is designed by adjusting the coefficients so that the mean square value of the output error sequence is minimised, and modified the weights based on this data. The iterative formula of the LMS process is as follows



4 Neural network adaptive filter model

$$y(n)=\sum_{\mathrm{i}=1}^{\mathrm{M}-1} w_{\mathrm{i}}(n)u(n-i)+\mathrm{b} \tag{4}$$

$$e(n)=d(n)-y(n) \tag{5}$$

$$w_{\mathrm{i}}(n+1)=w_{\mathrm{i}}(n)+2\delta e(n)u(n-i) \tag{6}$$

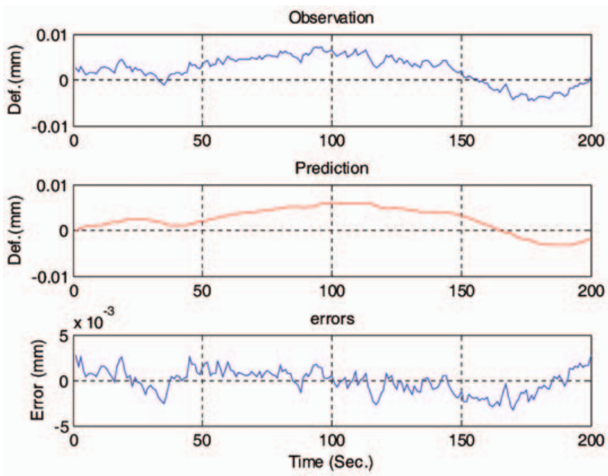
where, w is the filter weight coefficient; δ is the step; M is the filter order; and b is the neural constant.

The NN is used to implement AF algorithm LMS, that is, the network is used to solve least squares problem, as solutions

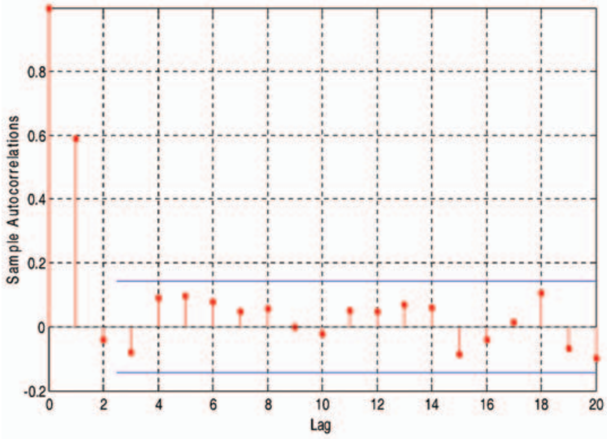
$$\begin{aligned}&\min \sum_{\mathrm{n}=\mathrm{N}-1}^{\mathrm{N}} |d(n)-y(n)|^2=\\&\min \sum_{\mathrm{n}=\mathrm{N}-1}^{\mathrm{N}} \left|d(n)-\sum_{\mathrm{i}=1}^{\mathrm{N}} w_{\mathrm{i}}u(n-i)+\mathrm{b}\right|^2\end{aligned} \tag{7}$$

Analyse the model

In this section, sample data from bridge Zhujiang Huangpu GPS health monitoring observations were used with 200 recorded second. The prediction and errors signals are calculated by NNAF model. Figure 5 shows the observation, prediction and errors signal of the measurements data. From Fig. 5, it can be concluded that the errors, which on the third row, are uncorrelated signal outputs, which contain mainly



5 Observation, predicted and errors of GPS signals



6 ACF and 95% confidence errors intervals of neural network adaptive filter model

receiver noise for this short baseline and unfiltered multipath residuals, and this result is cited in Roberts *et al.* [**24**] which confirmed this fact. In addition, it can be seen that the NNAF model smoothed the observation data, whereas the standard deviation of the smoothed data is decreased by 3·5%, which means that the NNAF can be used to eliminate the errors due to receiver and multipath errors and to smooth the GPS observations. Also, the R-square for the predicted model is 0·90 which indicates that the balance between the observations and the predicted signals is high and the predicted signals expressed the bridge movements. In addition, Fig. 6 shows the auto-correlation function (ACF) of the residuals. From Fig. 6, it can be shown that the value of AC falls within 95% of the confidence interval, therefore the residuals for the NNAF remained in the boundaries of the ACF confidence interval and there was no loss of information in the description of the signal. The calculated mean square of regression errors is $7{\cdot}84\times10^{-6}$, which means that the prediction model is more accurate. These results can be concluded that the NNAF model can be used to de-noise the GPS health monitoring signals. In addition, the predicted signal from the model expresses the movements of structures.

Long-span bridge deck movement analysis

The movements of Zhujiang Huangpu Bridge deck analysis are described in this section, as shown in Fig. 1. Two mid span points (103) and (108) are selected. The statistical moments of the time history of the GPS coordinates and the time–frequency of the data for the selected points will be used in this analysis. The mistakes of the recorded measurements should be removed before applying the analysis; therefore the relative GPS observations which increased more than three times of the standard deviation of the signal observations will be removed [**11**], [**6**], [**19**].

Time-series statistical moment bridge deck analysis

As the interface between two surfaces in motion begins to break down, the shape of the probability density function changes and tends to become more peaky [**16**]. This change can be monitored using the fourth statistical moments [**7**], [**16**]. The first four statistical moments [mean, standard deviation (SD), skewness (S), and kurtosis (K)] are often computed when examining raw time-series data. A brief review on the first four moments is shown in the following references [**7**], [**17**], [**16**].

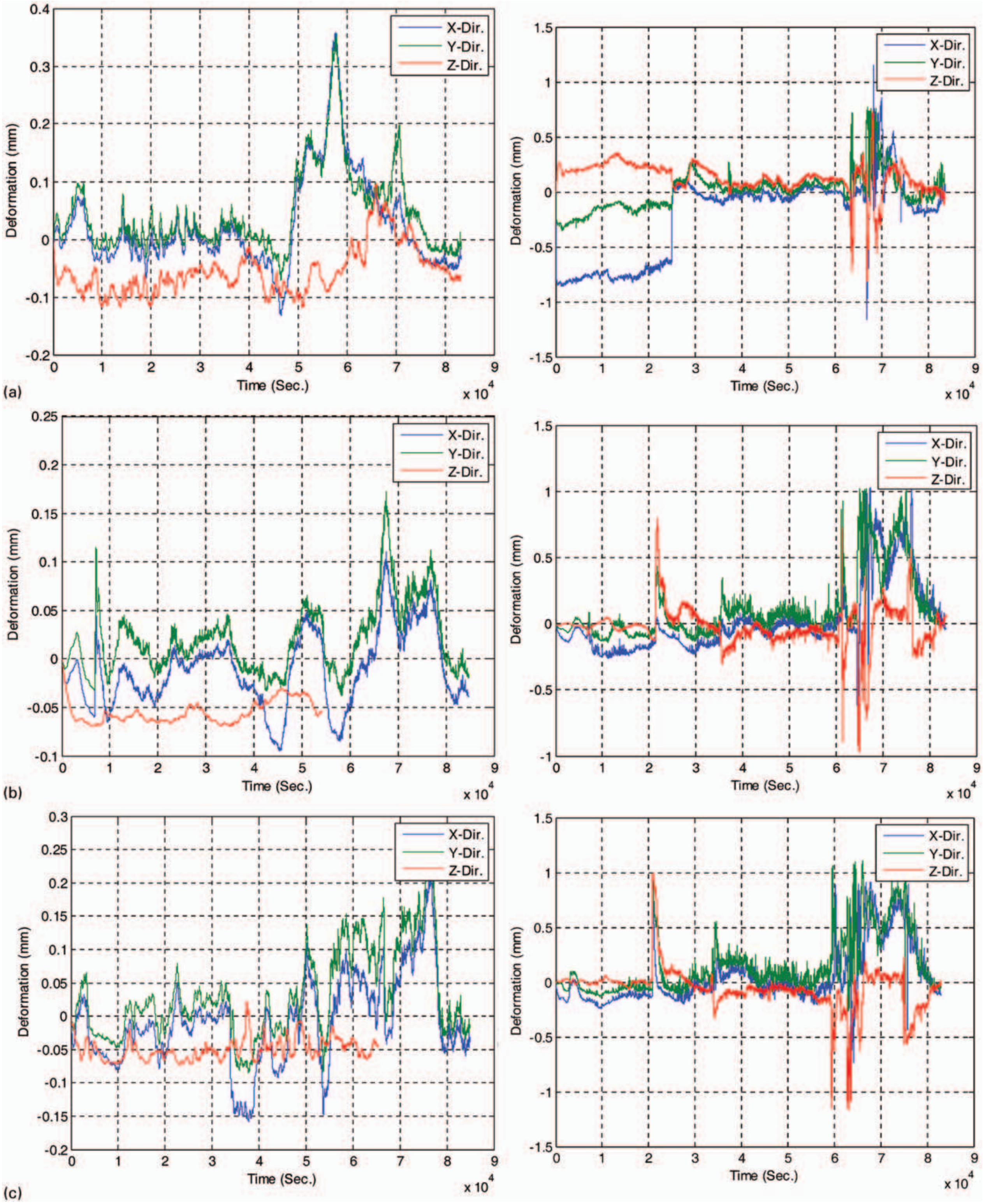
This section is concerned with the extraction of basic signal statistics as movement sensitive features. In order to show an overview of the raw data's appearance, GPS-time, predicted by NNAF model, histories of stages no. 1 to no. 8 from days: 15th, 24th and 26th of September 2009, every stage is about 2·8 h, GPS observation are plotted as two points (103) and (108), in a concatenated form. Figure 7 shows GPS RTK signal of moving state and Fig. 8 shows GPS RTK signal of stationary state condition.

From Fig. 7, it can be seen that the amplitude of the time histories is relatively consistent, based on visual inspection. Also, it can be shown that the correlation between x and y direction is high in the two mid span points, whereas the z direction movements are highly correlated with X and Y directions at point 108. In addition, the Z movement value at point 103 is normally about 0·05 mm whereas it is about zero at point 108. The movement's values at point 108 are greater than point 103 movements due to the length of span. In addition, it can be shown that the movement's values increased from 6 to 8 stages every day at the two points. It means that the traffic loads affect the bridge movements at these stages. In addition, it can be seen that the NNAF model can be smoothed and predicted the GPS signals with high correlation. In addition, the R-square values of the three directions on the three days are greater than 0·93.

In addition, from Fig. 7, it can be shown that the GPS observation on 15th September at point 108 has errors in the first three stages. In addition, it can be shown that the maximum displacement of Zhujiang Huangpu Bridge is 1·17 mm at point 108. It means that the maximum displacements are smaller than the accuracy of GPS used. From these results, it can be concluded that the movements of the two spans are safe and within the allowable values during the different loading cases; whereas the maximum deformation values for the long span at point 108 is + 0·50 mm and at point 103 is + 0·10 mm, also the GPS is high sensitively under effective loads. In addition the NNAF model can be used to simulate the GPS deformation signal with high accurate.

Figure 8 also represents the first four statistical moments of the three days time histories of the GPS observations. The mean and SD of the time histories are give insight about the presence of nonlinearities associated with the movement stage conditions (stages no. 7, no. 15 to no. 16, no. 23 to no. 24). However, there cannot be given response for the damage states [**7**]. In the other hand, the S and K do not show any difference in the movement states for the three monitoring day observations, which means that the movements of the bridge decks are not high effective. While, it can be shown that the stage conditions (stages no. 19 and no. 22) are different for other stages, it is due to the GPS signal errors. In addition, the S and K are sensitive to the errors of GPS observation stages no. 1 to no. 3. Whereas, the S values are 6·00, 0·88 and −0·01, and the K values for these stages are 75·74, 3·57 and 1·03, respectively.

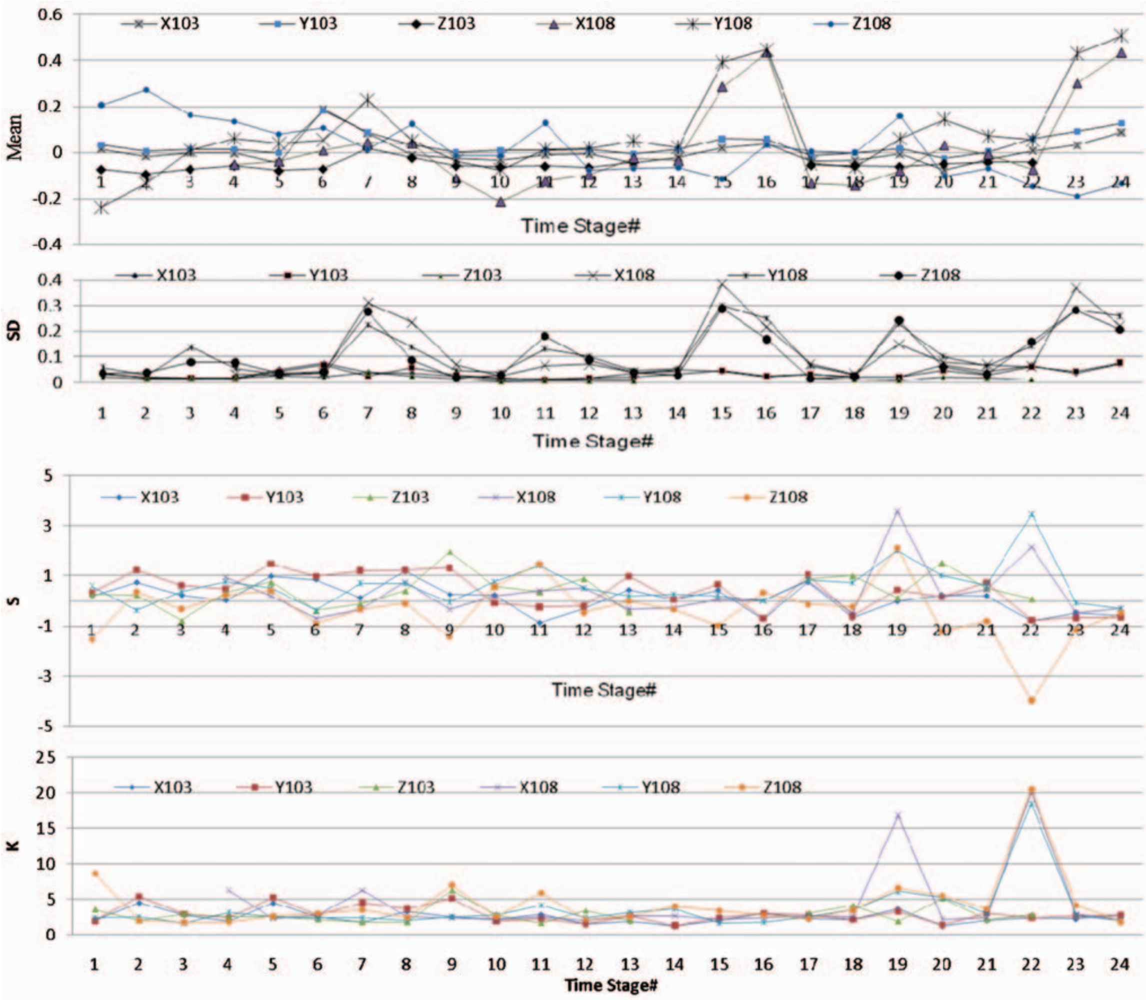
From Fig. 8 it is clear that for almost all of the GPS observation movements, the S diverges from zero, with



a September15; *b* September 24; *c* September 26

7 GPS RTK signal of moving state points 103 (left) and 108 (right)

the possible exception to stages no. 19 and no. 22. It is of interest to note that the S has an opposite sign for the GPS signal errors and movements due to impact loads, implying that the response from Z direction at point 108, has more values below the mean in its movement and errors condition, vice versa the Z direction at point 103 has more values above the mean. Moreover, in general these same movement states have larger K (larger than 3·5) than the un-movement stage, and this result is cited in Martin *et al.* [**16**]. Note that the K is larger than 3 which means that most of the variance is caused by non-frequent extreme deviations from the mean. However, for both S and K values the changes are significant in the movement and error effect. This fact points out the challenge of using GPS observations to detect the structural movements and GPS signal errors. In conclusion, the skewness and kurtosis can be used as features to detect movement that results in a linear system



8 First four statistical moments for GPS RTK signal of stationary state condition

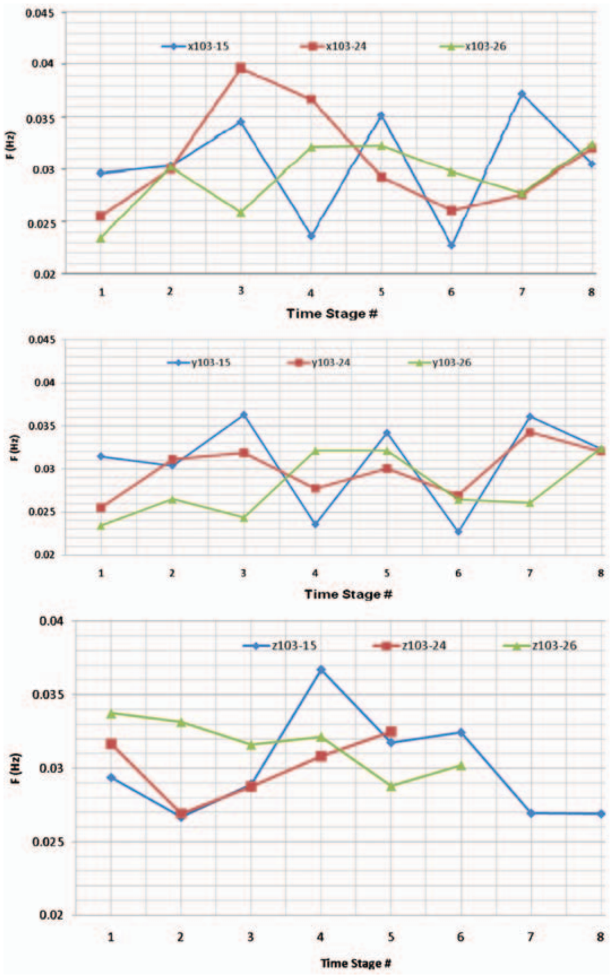
subsequently exhibiting nonlinear dynamic response and the GPS errors can be predicted. In addition, the skewness and kurtosis can be used to expect the state of movements. Also the mean and standard deviation can be referred to the movements of the structures only.

Bridge deck time–frequency analysis

Time–frequency analysis is to study the signal in both the time and frequency domains simultaneously. The main advantage of this representation is to track the evolution of the frequency components of the signal over time. For stationary signals, the frequency content should not change over time and vice versa for non-stationary signals [7], [17]. The important parameters that influence the dynamic response of the long-span bridges are vehicle speed, road surface roughness, vehicle characteristic, vehicles numbers and their travel path and bridge structure characteristic such as the bridge geometry, support condition, bridge mass and stiffness, and natural frequency [13]. In this study, after using NNAF model for the signal prediction, the bridge deck frequency components in the time domain for the longitudinal (X), lateral (Y) and vertical (Z) directions were determined by using the fast Fourier transformation based on Hamming window and band-pass filter for the frequency range 0·02–0·3 Hz. The calculated frequency modes are affected by the high frequency changes which occur over long-term movements as a result of random or instantaneously changing loads affecting the bridge. The following figures show the time–frequency plot of the deck movements for the three days analysis.

From Figs. 9 and 10, it can be shown that the first mode frequency only appears clearly at point 103 while the first and the second mode frequencies can be determined clearly at point 108. From Fig. 9, it can be seen that the maximum frequency in X direction at point 103 is 0·039 Hz and the minimum frequency for three days is 0·023 Hz. In addition, the maximum and minimum values for three days in Y direction are 0·036 and 0·022 Hz, respectively, whereas in Z direction these values are 0·036 and 0·025 Hz. These values refer to the maximum and minimum values of the first mode of bridge are close; it implies that the movement of bridge deck at point 103 is a safe mode on three dimensions, and correlated.

From Fig. 10, it can be seen that the second mode frequency of GPS signal movement on three dimensions is very close to 0·15 Hz. In addition, the maximum and minimum first mode frequency on X, Y and Z directions at point 108 for three days are 0·032, 0·037, 0·037 and 0·020, 0·21, 0·20, respectively. From these results it can be seen that the maximum values are very close. Also the minimum values are very close too, and this is refer to the movement of bridge deck at point 108 is very safe at two modes and correlated. From Figs. 9 and 10, it can



9 First mode frequency of X, Y and Z directions for days 15th, 24th and 26th September at point 103

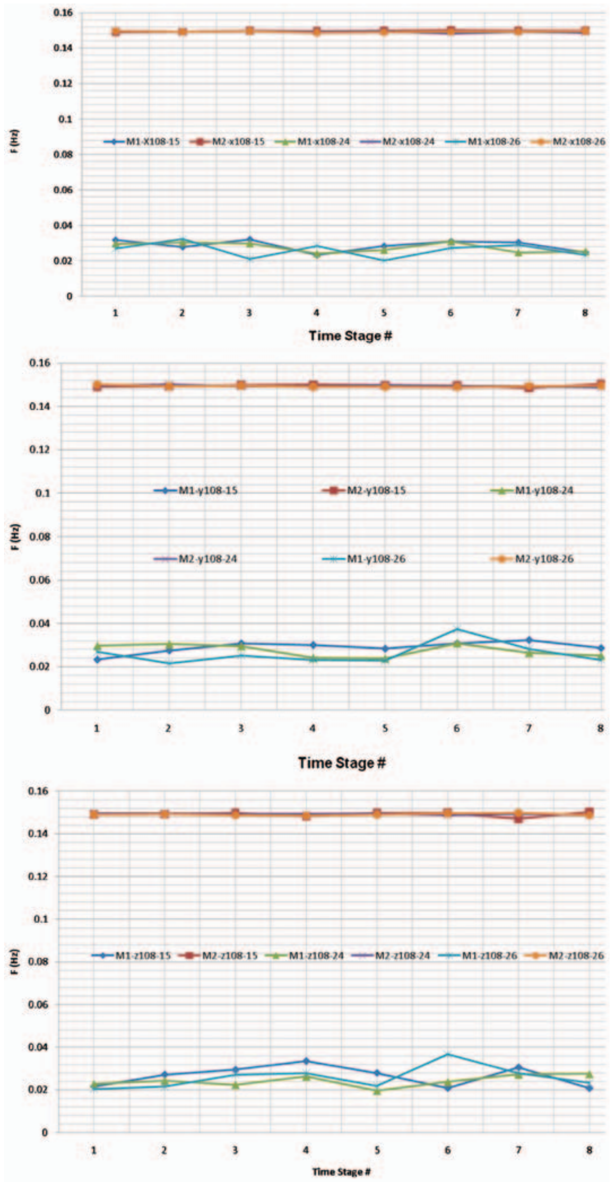
be seen that the first mode of bridge monitoring points has some changes along monitoring days. That means that the vehicles (vehicle speed, vehicle characteristic, vehicle number and their travel path) affect the frequency modes of the bridge deck.

From Figs. 9 and 10, it can be concluded that the bridge deck movements in three dimensions of GPS monitoring at points 103 and 108 are very safe. In addition, the length of span has an effect on the mode frequencies of structure based on GPS monitoring signals. Also, the GPS signal frequency modes are not influenced by GPS signals errors; therefore, time–frequency analysis can be used to study the structures' movement based on GPS signals. In addition, the movement of bridge deck is correlated in the three dimensions.

Conclusions

In this study, GPS observations and NN with AF are proposed to analyse and predict the movements of the Zhujiang Huangpu Bridge. The analyses in the time and frequency–time domains have been used to predict the GPS signals. Based on this limited study, the analysis of the results leads to the following findings.

1. The NNAF model can be used to de-noise the GPS health monitoring signals. Also, the predicted signals from the model were expressed the movements of structures.



10 First (M1) and second (M2) mode frequency of X, Y and Z directions for days 15th, 24th and 26th September at point 108

2. The errors due to receiver noise and multipath residuals can be separated from GPS signal observation using NNAF model.

3. The RTK GPS with 1 Hz observations show high sensitivity for the movement of structure; therefore, it can be used in the structural health monitoring of the bridge deck to remove the signal noises.

4. The time series analysis for the four statistical moments (mean, standard deviation, skewness and kurtosis) can be used to detect the movement of structures.

5. The time series skewness and kurtosis can be used to detect the GPS observation errors, in this study, it can be seen that the kurtosis was higher than 3·50 due to the GPS signal errors. Whereas, the skewness value within $\pm 1{\cdot}0$ refer to movements else refer to noise of signals.

6. The GPS movement observation signals in this study are considered stationary signals, almost.

7. The bridge deck is very safe at the two observation points 103 and 108.

8. The second mode frequency of the GPS observations can be clearly determined and identified for the long span bridge

9. The maximum and minimum frequency for the first mode at two points 103 and 108 are very close, whereas the second mode frequency is approximately 0·15 Hz, with the time at point 108.

10. The mode frequency of GPS signal is not influenced by errors of the GPS signals, so time–frequency analysis can be used to study the structures movement based on GPS observations.

Herein, it can be suggested that the time-series of skewness and kurtosis can be used to detect the structures damage using GPS monitoring system.

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