A NEURAL NETWORK RELATION OF GPS RESULTS WITH CONTINENTAL HYDROLOGY

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ABSTRACT. This paper presents the application of a neural network methodology to historical time series of GPS data from the IGS (International GPS Service) network, based on terrestrial water storage information. Hydrology signals at the GPS sites are important for including water loading corrections in GPS data processing. However, it is quite common that a correct global water storage model may not be available for this purpose, due to lack of science data. It is therefore mostly assumed that water mass redistribution is one of the potential contributors to the seasonal variations in GPS station position results, particularly, in the vertical direction. Presently, the IERS Special Bureau for Hydrology (SBH) has archived continental water storage data from some of the latest model developments. Examples include the monthly (GRACE, NOAA CPC, NCEP/NCAR CDAS-1) and daily (NCEP/NCAR and ECMWF reanalyses) solutions. It is valuable to study the relationship between these solutions and long-term geodetic results, especially as the water storage models continue to be refined. Using neural networks offers an effective approach to correlate the non-linear input of hydrology signals and output of geodetic results by recognizing the historic patterns between them. In this study, a neural network model is developed to enable the prediction of GPS height residuals based on the input of NOAA CPC hydrology data. The model is applied to eight GPS sites with satisfactory results.

Keywords: continental water storage; geodetic time series; hydrological models; neural networks.

1. INTRODUCTION

Historical time series generated from GPS (Global Positioning System) sites reveal significant seasonal variations in the vertical direction, in particular, with an annual period. It is well known that continental waters (soil moisture, snow, ground water) mass redistribution is one of the potential contributors to these observed seasonal variations (Dong et al., 2002; van Dam et al., 2001). Reliable evaluation of the interrelations between anomalous vertical movements observed at geodetic sites and hydrological signals are necessary, in particular, as the hydrology models continue to be refined. Improvements in the water load estimation would eventually lead to a recommendation on the best procedure(s) for including water loading corrections into geodetic data.

Presently the IERS (International Earth Rotation Service) Special Bureau for Hydrology (SBH) distributes continental water storage data from some of the latest hydrology model

developments at <http://www.csr.utexas.edu/research/ggfc/>. The gridded datasets cover entire continents, except Greenland and Antarctica, with resolutions ranging from 1° ($\sim 100\text{km}$) to 2.5° ($\sim 200\text{km}$), at different time spans. Included are (a) the daily continental water storage from NCEP (National Centers for Environmental Prediction)/NCAR (National Center for Atmospheric Research) and ECMWF (European Centre for Medium-Range Weather Forecasts) reanalyses, (b) the monthly water storage anomaly from GRACE (Gravity Recovery And Climate Experiment) mission, and (c) monthly water storage from CPC LDAS (Climate Prediction Center Land Data Assimilation System) and NCEP/NCAR Climate Data Assimilation System I (CDAS-1) reanalysis. The NCEP/NCAR and ECMWF models produce atmospheric reanalysis of all available weather observations for the past several decades without coupling to ground water or continental ice sheets. It is particularly observed that NCEP/NCAR results are dominated by near-sinusoidal annual variations with very little inter-annual variation (Wilson and Chen, 2003). On the other hand, ECMWF water loads are not nearly so sinusoidal and seem to provide some inter-annual variability. The GRACE mission cannot provide the total continental water contents, but an anomaly field referred to as monthly water storage anomaly (Han et al., 2005). Although preliminary studies have shown the potential of GRACE for investigating inter-annual variations in terrestrial water storage (e.g., Tapley et al., 2004; Andersen et al., 2005; Velicogna et al., 2005), the time span is still fairly short at the time of this writing. The CPC LDAS is one of the land surface models developed at the US National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Center. The CPC LDAS model is forced by observed precipitation, derived from CPC daily and hourly precipitation analyses, downward solar and long-wave radiation, surface pressure, humidity, temperature and horizontal wind speed from NCEP reanalysis (see also <http://www.cpc.ncep.noaa.gov/soilmst/>). The output consists of soil temperature and soil moisture, the soil moisture, in cm of equivalent water thickness, represents the net water mass stored over the continental areas and islands. Elsewhere, other global land surface models are under development at various laboratories. Examples include the Geophysical Fluid Dynamics Laboratory (GFDL) model of Princeton University and NASA's Global Land Data Assimilation System (GLDAS). Water storage variations from an early version of the GFDL model were employed by van Dam et al (2001) to estimate load deformation at GPS sites.

In this study we adopt the monthly CPC model (Fig. 1) to assess the neural network relation between long-term GPS results and continental hydrology signals. Example data are taken from eight different locations around the world (Table 1), six at mid-latitudes (in Western Australia, North Eastern United States, Finland, Eastern Canada, Japan and China), and two equatorial sites (in Africa and South America). For these sites we adopt GPS time series generated at the Scripps Orbit and Permanent Array Center (SOPAC) in the form of daily solutions (<http://sopac.ucsd.edu>). The daily solutions are then averaged into weighted monthly estimates that correspond to the epochs of the water storage data. Both the resulting GPS time series and the water storage data are mean-centered and linearly detrended before being used in the neural network analysis. The GPS time series represent the residuals after known geophysical sources associated with the response of the earth to surface mass loading have been removed. The known geophysical sources include pole tides, ocean tides, atmospheric mass loading, non-tidal ocean mass loading, and are well studied by Dong et al. (2002). However, the loading-induced seasonal deformations from large-scale terrestrial water storage are the least well understood (van Dam et al., 2001) and a reliable global hydrological model is not yet available (Takle et al., 2005; Wilson and Chen, 2003). The term GPS height residuals is used to refer to the GPS height results with the known geophysical sources removed except those due to soil wetness (snow mass, soil moisture, ground water) and other unmodelled error sources. It is therefore assumed that water storage loading may be the cause of some of the long-period variability, which is observed in the GPS time series, especially

where the water storage loading effect is large. Fig. 2a – 2f shows the GPS height residuals for six GPS sites, with the corresponding hydrology signals from NCEP and CPC models. The daily NCEP signals are included only for comparison with their monthly CPC counterparts.

Fig. 1. CPC monthly water storage at epochs in summer and winter of 2001-2002.

Table 1. GPS Sites Used in This Study

Site	Location	Longitude	Latitude
YAR1	Yarragadee, Australia	115.3E	29.0S
WES2	Westford, USA	288.5E	42.6N
METS	Kirkkonummi, Finland	24.4E	60.2N
ALGO	Algonguin Park, Canada	281.9E	46.0N
TSKB	Tsukuba, Japan	140.0E	36.1N
LHAS	Lhasa, China	91.0E	29.7N
MALI	Malindi, Kenya	40.2E	3.0S
FORT	Fortaleza, Brazil	321.6E	3.9S

Fig. 2a. Hydrology and GPS signals at YAR1.

Fig. 2b. Hydrology and GPS signals at WES2.

Fig. 2c. Hydrology and GPS signals at METS.

Fig. 2d. Hydrology and GPS signals at ALGO.

Fig. 2e. Hydrology and GPS signals at LHAS.

Fig. 2f. Hydrology and GPS signals at MALI.

2. BACKPROPAGATION NEURAL NETWORK METHODOLOGY

As a supervised learning technique, neural networks were originally developed to simulate the function of a human brain or neural system. A general overview can be found in Bose and Liang (1998) and Wasserman (1993). Since neural networks have powerful capabilities as universal approximators of nonlinear mapping functions with arbitrary complexity, the approach has been widely applied to different fields of science and engineering (Hammerstrom, 1993). In analogy to the biological nervous system, a neural network (NN) model can learn, and therefore be trained to find solutions, recognize patterns and predict or

assess the system response to the input factors. In applying a trained and validated NN model, the output variables are directly calculated from input variables without iteration. Based on the fact that an error backpropagation learning algorithm is efficient in approximating any continuous functional mapping between nonlinear signals, a neural network of this type was employed to correlate the GPS height residuals with the corresponding hydrology signals. Fig. 3 shows the structure prototype of such a network composed of a sequence of layers that are classified as input, hidden and output layers.

Fig. 3. Typical neural network prototype (left) and artificial neuron or node (right).

2.1. PROCEDURE

As shown in the previous section (Fig. 3), each layer of the network consists of a set of one or more neurons (or nodes). Each neuron has an activation function, which can be continuous, linear, or nonlinear [i.e., nonlinear function that saturates at finite value arguments like sigmoidal and tanh]. The neurons in the input layer receive information from the input variables, processes this information, and sends output to the next layer of neurons in the network. Each neuron is connected to neurons in the preceding layer, from which it receives inputs, and to the neurons in the subsequent layer, to which it passes its output.

The input layer data are multiplied by initial trial weights and a bias is added to the product. This weighted sum is then transferred through either linear or nonlinear transfer functions to yield an output. Thus, the output of a neuron in any layer is determined by applying a linear or nonlinear transformation (the activation function) to the sum of the weighted inputs it receives from the neurons in the previous layer. This output then becomes the input for the following hidden layers and the procedure is continued till the output layer is reached. The difference between the network output and the target is used to determine an error function, and the error is propagated back (“backpropagation”) to update the weights and biases using an optimization technique like the gradient descent which strives to minimise the error. The entire procedure is repeated for a number of epochs till the desired accuracy in outputs is achieved (“training”). Once the network is trained it can be used to validate against new data using the trained weights and biases. During validation, the model output variables are directly calculated, without iteration, from the input variables and the trained weights and biases, thus taking much less computation time.

Mathematically, the training process is similar to approximating a multivariable function (GPS height residuals), $g(X)$, by another function $G(W, X)$, where $X = [x_1, x_2, \dots, x_n]$ is the input

vector (hydrology signals), and $W = [w_1, w_2, \dots, w_n]$ the coefficient or weight vector. The training task is to find the weight vector W that provides the best possible approximation of the function $g(X)$ based on the training input $[X]$. By using the gradient descent method, weight changes move the weights in the direction where the error declines most quickly. Training is carried out by assigning random initial weights to each of the neurons (usually between 0.1 and 1.0) and then presenting sets of known input and *target (output)* values to the network. The network estimates the output value from the inputs, compares the model predicted output to the target value, and then adjusts the weights in order to reduce the mean squared difference between the network output and the target values. The complete input-output sets are run through the network for several iterations (or epochs) until either the mean square error is reduced to a given level or reaches a minimum, or until the network has been trained for a given number of iterations.

If we let w_m represent the value of weight w after m th iteration in a neuron, then

$$w_m = w_{m-1} + \Delta w_m \quad (1)$$

where Δw_m is the change in the weight w at the end of iteration m . It is calculated by

$$\Delta w_m = -\varepsilon d_m \quad (2)$$

where ε is the user-specified parameter controlling the proportion by which the weights are modified. The term d_m is given by

$$d_m = \sum_{n=1}^N \left(\frac{\partial E}{\partial w_m} \right) \quad (3)$$

where N is the total number of data samples and E is the network output error.

2.2. MODEL IMPLEMENTATION

In neural network development, the first step is to design a specific network architecture that includes a specific number of layers. The size and structure of the network needs to match the nature of the investigated phenomenon. Because it is usually not well known at the early stage, the task is not easy and often involves a trial and error approach. The new network is then subjected to the training process. In that phase, the neurons apply an iterative process to the number of inputs to adjust the weights of the network in order to optimally predict the sample data on which the training is performed. After learning from an existing data set, a separate new data set is used to validate or verify the performance of the trained neural network. If the network performance is satisfactory in model verification, it is capable of predictions using new data inputs.

2.3. PERFORMANCE CRITERIA

The objective of the training phase is to produce a set of weights that causes the outputs to match as closely as possible the observed system output. Achievement of this objective is typically measured by the correlation coefficients (R). However, this coefficient is not a robust measure of the model predictive capabilities since it is sensitive to outliers and spurious data. Therefore, the following other error measures may also be employed in the evaluation of the model: the Root Mean Square Error (RMSE), the Coefficient of Efficiency (CE), and Index of Agreement. Their mathematical formulation can be found in Khalil et al (2005). Bias and mean absolute error are also physical measures. Bias is the average of the difference between observed and predicted values, while mean absolute error is the average of the absolute of the residuals. For more details about goodness-of-fit measures, see David and Gregory (1999).

2.4. OPTIMIZATION AND IMPROVEMENT

The standard gradient-descent training method sometimes suffers from slow convergence due to the presence of one or more local minima. There are several optimization methods that can be used to optimize the convergence speed and performance of the network training. Details of the optimization algorithms have been described by Haykin (1999). Another problem that may occur during network training is overfitting. The error on the training set is driven to a very small value, but when new data is presented to the network, the error is large. In this case the network has memorized the training examples, but has not learned to generalize to new situations. One useful approach for improving the network generalization is to use an adequately sized network that is just large enough to provide an adequate fit. The larger a network is, the more complex the functions that the network can create, which may lead to overfitting. If a small enough network is used, it will not have enough power to overfit the data. However, it is difficult to know beforehand just how large a network should be for a specific application. In general, the optimal network size to prevent overfitting can be determined through model sensitivity experiments.

3. RESULTS

The standard three-layer backpropagation network was employed for each GPS location. Log-sigmoidal and tan-sigmoidal activation transfer functions were used for the hidden and output layers, respectively, and the input-output decks were scaled to a $[-1, 1]$ range. All computations were done using the Matlab computer software (Mathworks, 2004). Each network was trained using one data set and then validated with another data set (Table 2). Through sensitivity study, the optimal network size was selected as that size which resulted in the minimum error and maximum correlation in the validation data set. A network with 30 input nodes, 1 hidden node, and 1 output node was adopted. Default model parameters are given in Table 3.

Table 2. Input-output data required for model training and validation.

	Network input	Network target/output
1. Model training	<i>dataset-1-CPC</i>	<i>dataset-1-GPS</i>
2. Model validation	<i>dataset-2-CPC</i>	<i>dataset-2-GPS</i>

Table 3. Default parameters in the NN model for network training.

Parameters	Description
Optimized training method	Gradient descent
Number of nodes in input-hidden-output layers	30-1-1
Training goal	0.01
Training epochs	500

In the model training and validation phases, two independent sets of input and output time series are required in the NN model. For each location, the first 60% (~6 years) of hydrology data values were regarded as input and the corresponding GPS height residuals were treated as output. The subsequent 40% of the input and output pairs were then used to test (validate) the networks. Comparison of model predictions and observations during training and validation phases are given in Fig. 4a – 4f for the selected six GPS locations. In each figure, the time series used for training and validation are separated by vertical solid line. Results show that the neural network model was satisfactorily trained to determine the weight parameters in the network so that the inputs match well with the target time series. Thus the backpropagation neural network model was trained to recognize the time series pattern. Keeping the same weight parameters determined in the training phase, the model was able to

provide satisfactory predictions for an independent data set during the validation phase. The model track the observed residuals reasonably well at all of the GPS sites, demonstrating that water storage loading may indeed be the cause of some of the seasonal variability which is observed in long term GPS time series (see also van Dam et al., 2001). The correlation coefficients between the model predictions and observations ranged from 0.5 to 0.6 for all the stations at 95% confidence level. The RMSE were all approximately 4.8 mm. A summary of the statistics of the model performance is given in Table 4.

Fig. 4a. Hydrology, GPS, NN model (YAR1).

Fig. 4b. Hydrology, GPS, NN model (WES2).

Fig. 4c. Hydrology, GPS, NN model (METS).

Fig. 4d. Hydrology, GPS, NN model (ALGO).

Fig. 4e. Hydrology, GPS, NN model (LHAS).

Fig. 4f. Hydrology, GPS, NN model (MALI).

Table 4. Statistical summary of comparison between model predictions and observations

Site	Location	Training period	Validation period	Correlation value (R)	Root-mean-square error (mm)
YAR1	Yarragadee, Australia	1996-2002	2002-2004	0.6 (95%)	3.8
WES2	Westford, USA	1993-1999	1999-2002	0.6 (95%)	3.3
METS	Kirkkonummi, Finland	1996-2002	2002-2004	0.6 (95%)	3.5
ALGO	Algonguin Park, Canada	1996-2002	2002-2004	0.6 (95%)	5.1
TSKB	Tsukuba, Japan	1996-2002	2002-2004	0.5 (95%)	6.4
LHAS	Lhasa, China	1996-2002	2002-2004	0.6 (95%)	5.0
MALI	Malindi, Kenya	1996-2002	2002-2004	0.6 (95%)	5.0
FORT	Fortaleza, Brazil	1996-2002	2002-2004	0.5 (95%)	6.8

4. SUMMARY AND CONCLUSION

A neural network model has been used to evaluate the possible seasonal relation between the long-term GPS time series from SOPAC and continental water storage from NOAA CPC LDAS hydrology model. The commonly used three-layer backpropagation neural networks with log-sigmoidal transfer function in the hidden layer and tan-sigmoidal transfer function in the output layer, were employed in this case study. In general, satisfactory results were produced with the values of correlation coefficients equal to ~ 0.6 (95%) and RMSE of about 15% of GPS residual range (residual range = 20.6 to 35.6mm, mean ~ 27.4 mm).

The neural network model was able to successfully transform observed input vectors into reasonably accurate estimation of the outputs for all the locations. Its adequacy is demonstrated by the quality of the estimates as discussed above. However, the result from this study is not directly comparable with results from estimation of water load deformation, for example, as presented in an earlier study by van Dam et al (2001). Nevertheless it demonstrates that there is an underlying significant relationship between the GPS height residuals and the CPC LDAS water storage variations at the sites that have been analyzed. Other potential errors sources contributing to the GPS height residuals would include bedrock thermal expansion, errors in phase center variation models, errors in orbital modelling, the effects of employing different analysis strategies, and the unmodelled troposphere effects (Dong et al, 2002).

The proposed neural methodology can be applied to other geodetic time series (SLR (Satellite Laser Ranging), VLBI (Very Long Baseline Interferometry), Absolute Gravity) and hydrological models (GLDAS, GRACE, etc) provided site-specific training and validation are carried out appropriately. Similarly, due to the direct relation between water loading, precipitation and water vapor content, it may also be feasible to evaluate the seasonal relation between GPS-derived water vapor and groundwater storage variations.

ACKNOWLEDGEMENTS

The author is grateful to Geoscience Australia for supporting this study. However the views expressed are those of the author and do not necessarily reflect the views of Geoscience Australia. The IERS Global Geophysical Fluids Center (GGFC) and SOPAC are respectively acknowledged for sharing their hydrological model and GPS results. Reviewer comments improved the paper.

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Received: 2005-10-19,

Reviewed: 2005-11-18, by W. Kosek,

Accepted: 2005-12-01.