Precise Orbital Prediction Using Artificial Neural Networks

By Hamad Yousif and Dr. Ahmed El-Rabbany

Abstract

Precise real-time GPS orbit is required for a number of applications, including real-time Precise Point Positioning (PPP), long range RTK and weather forecasting. At present, users may take advantage of the predicted part of the IGS ultra-rapid orbit for real-time applications. Unfortunately, however, the accuracy of the predicted part of the ultra-rapid orbit is limited to about 10 cm (the 24-hour predicted part), which is not sufficient for the above applications.

In this research a 6-hour predicted orbit was generated by extrapolating a concatenated group of previous precise ephemerides for 5 days. RINEX observation files corresponding to the same period of precise ephemerides were collected from globally distributed tracking stations. Using Bernese software, those observation files were utilized to make further improvement for the prediction. The resulted prediction was finally refined by implementing a modular, three-layer feed-forward back-propagation neural network.

1. Introduction

The call for an ultra-rapid product was initially announced at the IGS Workshop held at La Jolla, CA, USA in 1999. The ultra-rapid product was intended to satisfy the need for real-time and near real-time applications which could not be met by rapid and final products. The ultra-rapid ephemeris file contains a 48-hour arc in the sp3 format. The first 24-hour arc is obtained by fitting the data and products which are already available over the first 24-hour period while the next 24-hour is predicted. In Feb. 2000 (week #1050) the Jet Propulsion Laboratory (JPL) analysis center released its first ultra-rapid product twice a day at 00:00 and 12:00 with an accuracy of 20 cm – 40 cm for the fitted part and 50 cm for the predicted part ([IGSMAIL-2717] JPL ultra-rapid orbits). The product is available from JPL anonymous ftp site (ftp://sideshow.jpl.nasa.gov/pub/gipsy_products/). The Centre for Orbit Determination in Europe (CODE), an analysis center, started releasing their ultra-rapid product in June 2003. Today there are 8 analysis centers, which submit their ultra-rapid products to the IGS Analysis Coordinator (located at GFZ Potsdam, Germany, http://www.gfz-potsdam.de/pb1/igsacc/index_igsacc.html) to be combined on the basis of weighted averages (Beutler *et al,* 1995) to generate the official IGS precise ephemerides. The 12-hourly ultra-rapid product was switched to a 6-hourly product in week # 1276. Each analysis center implements its own physical models of geostationary forces, direct and indirect tidal effects, solar radiation pressure, relativistic effect, tropospheric delay and others, which is processed by a wide variety of softwares and procedures. As an example, JPL uses GIPSY/OASIS II for processing hourly RINEX data from several stations. The method is based on generating multiple orbital arcs by processing 3-hour observations using the JPL rapid solution/covariance to initialize the 3-hour orbital arc. These arcs are combined by a process called the inverse sequential smoothing process ([IGSMAIL-2717] JPL ultra-rapid orbits). The CODE procedure starts by preprocessing the phase observation in a baseline by baseline mode using Bernese 5.0. Cycle slips are detected and fixed using triple differences and bad data are removed. A 72-hour orbital arc is predicted using multiple previous precise orbits and RINEX data from several stations are used to improve the osculating orbital parameters for the predicted orbit. The long arc processed by CODE involves a robust and long-lasting model for solar radiation pressure, which justifies the adoption of 9 parameters SRP model in addition to ROCK4 and ROCK42 models (Dach *et al,* 2007). ESA/ESOC (European Space Agency/European Space Operation Centers) uses BAHN software to process RINEX data in a zero difference-ionospheric free combination. The pseudorange, phase observations and precise orbit ephemeris from 3 previous days are written to one file. This file is processed later with a group of other files such as station positions, satellite and station clock biases and satellite dynamic models to produce the ultra-rapid product (Romero *et al,* 2001). Geodetic Observatory Pecny (GOP) uses the same procedures and software adopted by the CODE to produce their ultra-rapid products (Dousa, 2003). Such variety of strategies and techniques adds to the advantage of IGS products' quality and reduces the possibility of having biased results.

Although the above-mentioned methods are highly efficient, their prediction accuracy is not high. The accuracy of the predicted part of the ultra-rapid orbit is limited to about 10 cm (predicted part), which is not sufficient for the above applications. To overcome this deficiency an ANN-based prediction model is developed in this paper. It is shown that the ANN-based prediction accuracy was found to be in the order of 3 cm. The reason behind using the ANN is its capability of detecting complicated nonlinearity underlying any data.

2. Artificial Neural Networks

The Artificial Neural Networks (ANN) is one of the most brilliant scientific achievements that is attempting to approach and simulate the biological brain potentials of learning, analysis, deduction and recognition. The idea of ANN was first brought to existence by Walter McClulloch, a psychiatrist, and Warren Pitts, a mathematician, who wrote the first paper of ANN in (1943) at University of Chicago, Haykins (1999). In contrast to digital computers where the data is saved and retrieved for further processing, the ANN, in turn, store knowledge that can be used for future purposes of modeling and reproduction. The

ANN acquires this knowledge through a complicated training process based on the contents and behaviour of the input data and desired output *(target),* see Figure 1.

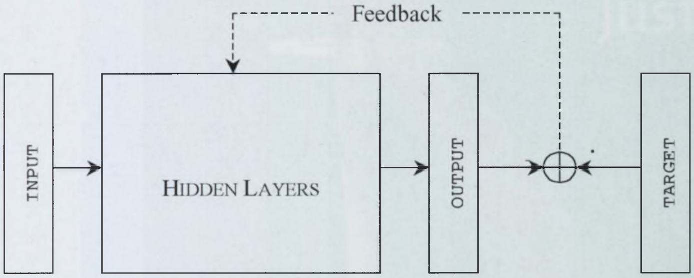


Figure 1. The basic units of ANN

The learning process starts by multiplying each of the input samples by *certain weights* (***w***) that are randomly initialized. The sum of these products for all the input samples in addition to an initial *bias* (***b***) are passed to a processing node (called a *neuron),* see Figure 2. The output of each neuron at a particular layer is passed to the next layer through a *transfer function* (***f***) – also referred to as *activation function.* A single layer with a nonlinear transfer function is called a *perceptron.* According to Civco and Waung (1994), "The transfer function is required to avoid saturation of a processing node, caused by extremely large positive or negative internal summations". This process is performed all the way down to the output layer where the error between the *output* and *target* is compared to a predefined amount (called a *goal)* to check whether the desired accuracy is reached. The previously mentioned error is equal to the sum of the square differences for all of these samples. If such difference is found to be less than the predefined goal, then it is fed back (or *back-propagated)* to establish a new iteration by updating the previous weights. The back-propagation algorithm is thoroughly discussed by Rumelhart (1986), Bishop (1995) and Ripely (1996). Basically, there is no standard or unique learning algorithm for all types of ANN (Haykins 1999), however a successful learning algorithm must improve the network knowledge through the weight adjustment procedure such that the output converges appropriately to the desired target.

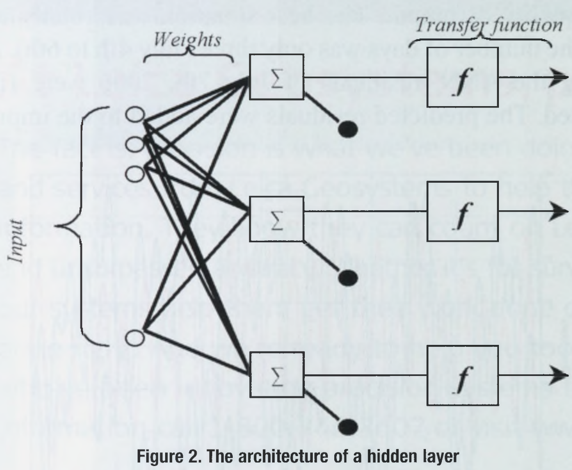


Figure 2. The architecture of a hidden layer

Most ANN package developers provide the user with a freedom to initialize and modify ANN parameters such as *goal, learning rate, number of iterations, transfer function, number of hidden layers, number of neurons per layer,* and other parameters, through a user interface facility to feature more flexibility and interaction. This is because the default parameters - even though it appeals to many users - may not always fit every type of data. The effectiveness of ANN has made it popular in a wide variety of applications ranging from engineering, science, economics, etc. For instance, in geomatics, the ANN was implemented by Miima *et al* (2001) for modeling geodetic deformations; Schuh (2002) for Earth orientation parameters; El-Rabbany *et al* (2002) for predicting sea ice condition; El-Rabbany and El-Diasty (2003) to obtain accurate tide predictions; and Kavzoglu and Saka (2005) to model local GPS/leveling geoid undulations.

3. Prediction Strategy

The prediction process in this research is performed into two different steps. The first step employs Bernese 5.0 software to generate a 24-hour orbit ephemeris using IGS precise products (ephemerides, clock corrections, ERP files) and RINEX observation data prior to the day to be predicted. The second step utilizes the power of Artificial Neural Networks to improve the previously generated ephemeris.

3.1 Part One: Orbit Prediction using Bernese Software

The GPS satellite orbit prediction by Bernese can be summarized into three main steps (Dach *et al,* 2007):

Here are the detailed procedures of each step:

a. Preparation of a priori orbit positions and partial derivatives with respect to orbital parameters

- The procedure starts with importing precise ephemerides for *five* days prior to the day to be predicted.
- Each of those precise ephemerides is converted to Bernese *tabular format.*
- The satellite clock correction coefficients are also extracted from each IGS precise ephemeris, combined, fitted to 2nd degree polynomial and stored into a **.CLK* file so that they can be used later within the course of generating the predicted orbit.
- Then a second subroutine is performed to concatenate and fit the precise ephemeris to a curve of 10th degree polynomial and extrapolate that curve to an additional 24-hour orbit which represents the day to be predicted. That curve does not exactly fit the concatenated precise ephemeris. In other words there are some residuals between the curve and the concatenated ephemeris. Figure 3 shows an example of those residuals.
- The former subroutine also takes partial derivatives of the orbit coordinates with respect to the orbital parameters (only the six *Keplerian* parameters) and fits them to a 12th degree polynomial at 6-hour intervals.
- The coefficients of the ephemerides polynomial are stored to a binary **.STD* file called a standard file while the coefficients of the radiation pressure are stored in a binary **.RPR* file. The partial derivatives of the satellite positions with respect to the radiation pressure coefficients as well as the partial derivatives of the satellite positions with respect to the *six Keplerian* parameters are contained in this**.RPR* file.

b. Estimation of improved orbit parameters using RINEX observation files

- RINEX observation files from 32 stations corresponding to the same period of the precise ephemeris are imported to Bernese. Figure 4 shows the distribution of those stations.
- The code observations are used for clock synchronization between receivers and satellites.
- Station baselines are created and a double difference is performed.
- After running this subroutine the improved orbit parameters are stored in a binary osculating orbital element file (**.ELE*).

c. Regenerate improved orbit

The orbital element file (**.ELE),* the standard file (**.STD),* the radiation pressure file (**.RPR)* and the satellite clock correction file (**.CLK)* are all used to update the a priori orbit ephemeris. After updating the orbit the residuals exhibit some improvement as shown in Figure 5.

3.2 Part Two: Prediction Enhancement using Artificial Neural Networks

o The residuals between the *five* precise and fitted ephemerides are calculated.

o Those residuals are used to train a feed-forward back-propagation neural network.

o After training the network, the residuals of the new day are predicted.

o The predicted residuals are added to the predicted ephemeris of the new day to obtain its precise ephemeris.

4. Results and Discussion

The IGS precise rapid ephemerides for several days preceding the day to be predicted - which is July 7th, 2006 - were used. Making numerous trials, only five days of those ephemerides - starting from July 2nd to July 6th, 2006 - were found sufficient for the purpose of this research. The precise ephemerides were concatenated and extrapolated to generate a 24-hour orbit of July 7th, 2006 as described in 2.1 above. The resulting orbit, which combines the five plus the newly generated ephemeris, is called an *a priori orbit.* Figure 3 below shows the residuals of the a priori orbit compared to the corresponding precise rapid ephemeris before any improvement is applied. As shown from Figure 3, the predicted part was apparently far from the desired accuracy and therefore it had to be improved by a subsequent process. The RINEX observation file for several IGS stations were downloaded from (ftp://cddis.gsfc.nasa.gov/gps/data/daily/2006) for the period between July 2nd and July 6th, 2006. We found that the number of stations should neither be too low nor too high. If the number of stations is much greater than 30, then the process will be time and memory consuming. On the other hand, too few stations won't be adequate to produce a reliable solution. Performing many experiments, the number of stations was eventually settled to 32 global stations (see Figure 4). The RINEX observations were processed to produce the osculating orbital element file, which was used to improve the a priori orbit in the final step. Figure 5 shows the residuals of the a priori orbit after improvement.

At this point, the prediction should be subjected to further

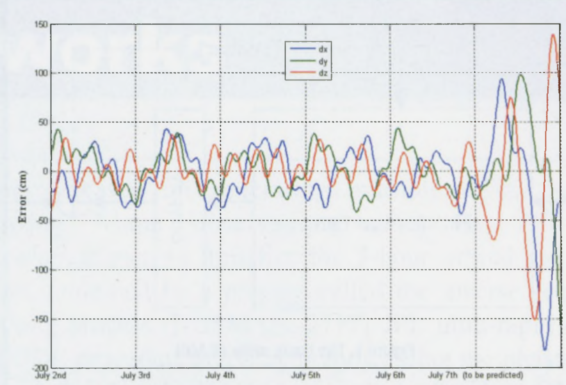


Figure 3. The residuals of the a priori orbit before orbit improvement


Figure 4. Distribution of selected stations

enhancement. Almost all predicting strategies apply sophisticated procedures to model the stochastic parameters of an orbit ephemeris. As compared to the standard mathematical methods which goes no further than data curve-fitting based on the rule (the most adjacent are the most relevant), ANN not only curve-fits the data but also detects the correlation of that data. In other words, ANN curve-fits the correlation itself on a weight basis, computes the stochastic parameters and restores them during prediction. Those were the very reasons that ANN was resorted to in this research where the residuals of five preceding days were used to train the ANN.

The ANN notoriously consumes computer resources when the training data is relatively large. Therefore attempts were made to compact the amount of data and at the same time maintain a good quality of output. The best situation was finally found when the number of days was only three (July 4th to 6th). After training the ANN, residuals of July 7th, 2006 were finally produced. The predicted residuals were added to the improved

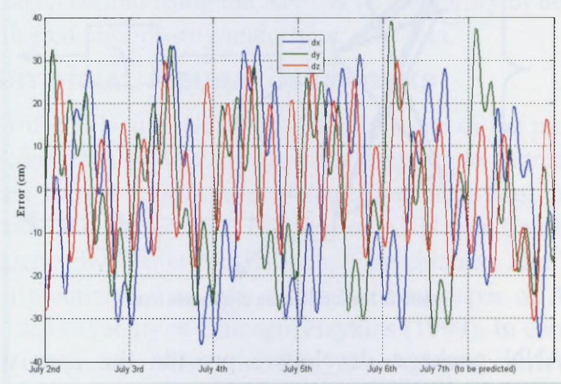
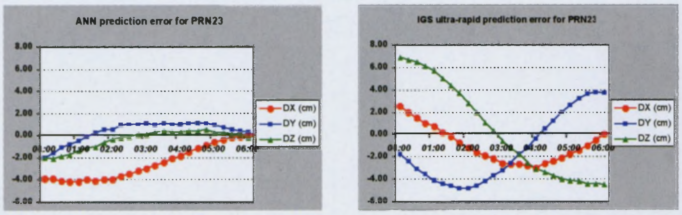


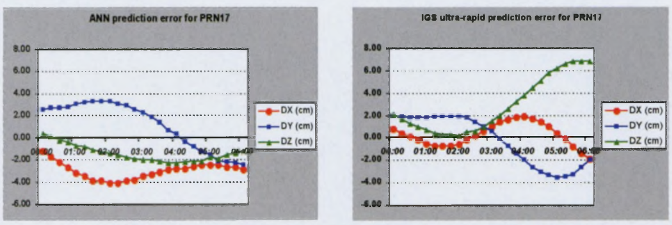
Figure 5. The residuals of the a priori orbit after improvement

orbit to obtain the rapid precise ephemeris of July 7th, 2006. The accuracy of this prediction for the first six hours of July 7th, 2006 is depicted in Figure 6 below. The accuracy tends to slightly degrade after hour 6:00. The same procedure was repeated for another group of data and ephemeris covering a span between Feb. 5th and Feb. 9th, 2007 to predict the first 6-hour arc of Feb. 10th, 2007. The prediction accuracy is shown in Figure 6.



	DX (cm)	DY (cm)	DZ (cm)
RMS	1.53	0.90	0.85
Overall RMS			1.96

DX (cm)	DY (cm)	DZ (cm)
1.61	3.06	4.22
Overall RMS		5.46



	DX (cm)	DY (cm)	DZ (cm)
RMS	0.74	2.14	0.77
Overall RMS			2.39

DX (cm)	DY (cm)	DZ (cm)
1.05	2.22	2.46
Overall RMS		3.48

Figure 6. The prediction accuracy of July 7th, 2006 (top) and Feb. 10th, 2007 (bottom)

Conclusions and Future Outlook

Artificial Neural Networks (ANN) proved to be powerful in GPS orbit prediction improvement. It has been shown that the obtained precision of ANN-based prediction is less than 3 cm, which is evidently superior to that of the IGS ultra-rapid. This makes the ANN-based prediction method more reliable than the IGS ultra-rapid product for real time applications. Future research will enhance the orbital prediction through the use of 35 well-distributed IGS tracking stations. In addition, Neural Networks will be applied to predict the clock corrections, which is expected to reflect positively on the prediction accuracy.

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