Fitness Analysis of Height Variation for GPS Monitoring Site

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Key words: land subsidence, artificial neural networ, grey theory, linear regression

SUMMARY

Due to the heavy withdrawal of underground water for cultivating fishery and industrial factories, the land subsidence occurred in southwestern Taiwan has resulted in environmental hazard and potential risk. In order to fully realise the subsidence characteristics and establish a subsidence prediction function for any possible application in the study area, the height variation was estimated and tested for the fitness at one of the representative GPS monitoring station, PKGM, using some selected models, i.e. the linear regression, neural network and grey theory. Since different estimation models associate with different time spans of the data, a series of GPS-based vertical coordinates was categorised into two groups of data set, namely a long-term (50-52 weeks) data set and a short-term (5 weeks) data set, both collected at PKGM for around 10 years (from 1995 to 2004). For using the long-term data set, the fitness tests showed that the neural network is able to provide an average RMS height estimation error of ±1.1 cm, slightly better than that of ±1.4 cm estimated by using linear regression. When testing the short-term data set, the estimation errors were found to be ±1.1 cm and ±1.2 cm for the results based on using linear regression and grey theory, respectively. This level of estimation fitness suggests that the short term of 5-week data is capable of working with a simple regression model for the prediction of height at the GPS site located in the significant land subsidence area.

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1. INTRODUCTION

It has been a long-term problem for land subsidence occurred in the alluvial fan of the Chuo-Shui River, a main river crossing the middle-south of Taiwan. It is believed that land subsidence is accompanied with heavy withdrawal of underground water near the coastal regions of Yun-Lin County (Liu et al. 2004). Among areas with soft ground features in this alluvial fan and a long history of underground water over-pumping, the land subsidence rate is generally up to a decimeter level per year (Chang 2000; Liu et al. 2001). Owing to the growth of population and the increasing need of fresh water for aquafarms, the situation has not been well controlled in the recent years. As a consequence, the subsidence area is even enlarged towards inland and potentially damages the engineering structure of the Taiwan High Speed Rail (Chang & Wang 2006).

As the geo-hazard of land subsidence is worth of noting, it is important to implement some of the geodetic techniques for the monitoring and understanding of land subsidence in the regions of interest. It is the fact that space geodetic techniques, particularly the Global Positioning System (GPS), have now almost entirely surpassed terrestrial methods for high accuracy geodetic monitoring (Herring 1999). The highest accuracy of GPS can be based on the observations made by the continuously operating GPS arrays (Bock et al. 1997). Nevertheless, the GPS monitoring campaigns with relatively less days and shorter observation sessions, based on either static GPS or kinematic GPS, are often carried on to more economically detect the 3-D coordinate variations for the monitoring sites. This cm-level of accuracy is basically sufficient for small scale of applications, such as the monitoring of landslide or ground subsidence (Bitelli et al. 2000; Sato et al. 2003).

There is, hence, a goal to establish a forecast technique by using a relatively short term of GPS monitoring data set to effectively estimate the up-coming level of land subsidence, in order to further prevent any associated problem and damage to the civil engineering structures. The aim of this paper is, hereby, to test the fitness of the selected models, such as the regression analysis, artificial neural network and grey forecast theory, with the continuous vertical monitoring data composed of either 5-week or 1-year GPS solution and collected at the representative site of PKGM in the land subsidence area.

2. ESTIMATION MODELS

2.1 Artificial Neural Network (ANN)

The model of artificial neural network, imitating human thought's pattern, induces an operation rule through learning process to build up its forecast and recognition capability (Hu et al. 2004)(Stopar et al. 2006). The ANN model consists of a pool of neurons or nodes as the simple processing unit. Each processing unit $\boldsymbol{X}_1, \boldsymbol{X}_2, \ldots, \boldsymbol{X}_n$ is mutually connected and linked to its weight $\boldsymbol{W}_{1j}, \boldsymbol{W}_{2j}, \ldots, \boldsymbol{W}_{nj}$, respectively. The operation output $\boldsymbol{Y}_j$ is the result of weighting product of input values through a transfer function $\boldsymbol{f}$ as

$$Y_j = f(\sum_{i=1}^{n} W_{ij} X_i - \theta_j) \quad (1)$$

where $\boldsymbol{W}_{ij}$ is the connected weight between layer node i and j, and $\boldsymbol{\theta}_j$ is the threshold of node j.

The multi-layered node model and error back propagation (BP) algorithm are normally applied by the ANN. It transfers a set of input/output samples into a non-linear optimisation process by finding rules from massive data. The advantages of using ANN for series data fitting are summarized as:

- The imitation capability for multi-functions, including non-linear and stepwise functions etc;
- To establish the function relations using variables' own attributes;
- To avoid the cancellation of a sequence of positive and negative values when accumulated.

A three-layer BP network, whose training process is composed of a forward and back propagation, can be shown in Fig. 1 for its three components, namely input, hidden and output layer.

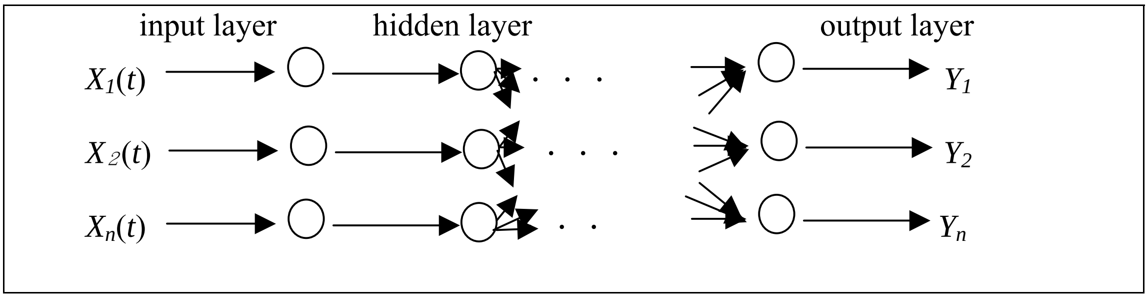

Fig. 1 Three layers of BP network

The learning algorithm of such an ANN model can be listed as follows:

1. To initialise with the random values: $\boldsymbol{W}_{ij}$ and $\boldsymbol{\theta}_j$;
2. To read the pre-processed training sample: $\{\boldsymbol{X}_{pl}\}$ and $\{\boldsymbol{Z}_{pk}\}$;
3. To compute the output of each node to p^{th} sample:

$$Y_{pj} = f\sum(W_{ij}(t)X_{pi} - \theta_j(t)) \quad (2)$$

where $\boldsymbol{X}_{pi}$ is not only an output of node i, but also an input of node j;

4. To compute the signal error of each node for

output layer: $\delta_{pk} = Y_{pk}(Z_{pk} - Y_{pk})(1 - Y_{pk})$ (3)

hidden layer: $Y_{pi} = Y_{pi}(1 - Y_{pi})\sum_i \delta_{pi} W_{ij}$ (4)

5. To process the back propagation for

weight updated: $W_{ij}(t+1) = \alpha\delta_{pj}Y_{pi} + W_{ij}(t)$ (5)

threshold updated: $\theta_j(t+1) = \theta_j(t) + \beta\delta_{pi}$ (6)

where α is a learning factor, and β is a momentum factor for rapid convergence;

6. To calculate the errors: the learning rule of back propagation is a process aimed at minimising the learning errors and adjusting the weights continuously. The difference between the network output (***Y***$_k$) and the desired value of training sample (***T***$_k$) is defined as the error function (***E)*** with

$$E = (\frac{1}{2})\sum_k (Y_k - T_k)^2 \quad (7)$$

Using a gradient descent method, the error function can be minimised to obtain the network weighting increment by

$$\Delta W = -\eta \frac{\partial E}{\partial W} \quad (8)$$

where η is a factor controlling the network learning rate.

2.2 Grey Forecast Theory (GFT)

The grey system theory was proposed by J. Deng in 1982 and initially applied by the time control domain. The grey forecast theory is worked with the raw data processing and the grey modelling to find and control the system development rules, and to make the effective forecasts for the future state. This model emphasizes that it can be modeling with very less data and can be used to estimate the variables for system's future behavior (Huang & Huang 1997).

For a common used model GM(l,1), it is approximate to be a differential model with the function of differential and exponential. The model parameters can be adjusted to reflect its time-variant structure. The GM(l,1) model is processed by three stages and described as follows:

1. Assimilation stage: taking GM (l,1) model as a classical mathematical model which is equivalent to a general differential equation, such as

$$\frac{dx}{dt} + ax = b, \hat{x}^{(1)}(k+1) = \left[x^{(0)}(1) - \frac{b}{a} \right] e^{-ak} + \frac{b}{a} \quad (9)$$

For a non-negative discrete sequence, its accumulation is monotonously increased in a concave type. Since the exponential curve has the same property, it can be fitting to the accumulated sequence. In addition, the solution of such a first order differential equation is also in an exponential type. It is, then, explained by taking this equation's discrete solution to describe the variation of the sequence accumulation. In the development point of view, this processing stage belongs to the initial stage.

2. Dissimilation stage: using grey model to gradually separate from the differential equation as

$$x^{(o)}(k)+az^{(l)}(k)=b \quad (10)$$

The GM(l,1) model is formed, in which the differential equation is then called the shadow equation. The GM(l,1) model is actually an approximate differential equation that is constructed by analysing the differential equation for the quality and characteristics.

3. Fusion stage: The solution is identified to the equation and satisfied with three conditions, i.e. the structure, material and quality. This higher level of processing stage has the form as

$$
\begin{aligned}
&x^{(1)}(k) + az^{(1)}(k) = b \\
&z^{(1)}(k) = 0.5x^{(1)}(k) + 0.5x^{(1)}(k-1) \qquad (11) \\
&z^{(1)}(k) = \sum_{m=1}^{k} x^{(0)}(m)
\end{aligned}
$$

2.3 Regression Analysis (RA)

In a regression equation, the dependent variable of y can be predicted by using a specific group of independent variables $\boldsymbol{t}_1, \ldots, \boldsymbol{t}_n$. It has been widely applied for many regression analyses. In this study, a simple type of linear regression equation is adopted and formed as

$$y_i = at_i + b \qquad (12)$$

where a, b are regression coefficients, representing the parameter of slope and intercept, respectively, in the linear model; $\boldsymbol{t_i}$ is defined as time variable and y_i is the height measured at the GPS site.

3. TEST RESULTS AND ANALYSES

The test data was collected from the GPS tracking station of Peikang (PKGM) located at the most significant land subsidence area in Taiwan (see Fig. 2). The data set is composed of 485 epochs of GPS weekly solution over the ten years from 1995 to 2004. It is obviously to see from the Fig. 3 that the height variation occurred at the test site presents a stable drop tendency. It is also realised that the temporal features of land subsidence appeared an average rate of 3 cm/year and a high correlation coefficient of 0.9 with the time (Chang & Wang 2006).

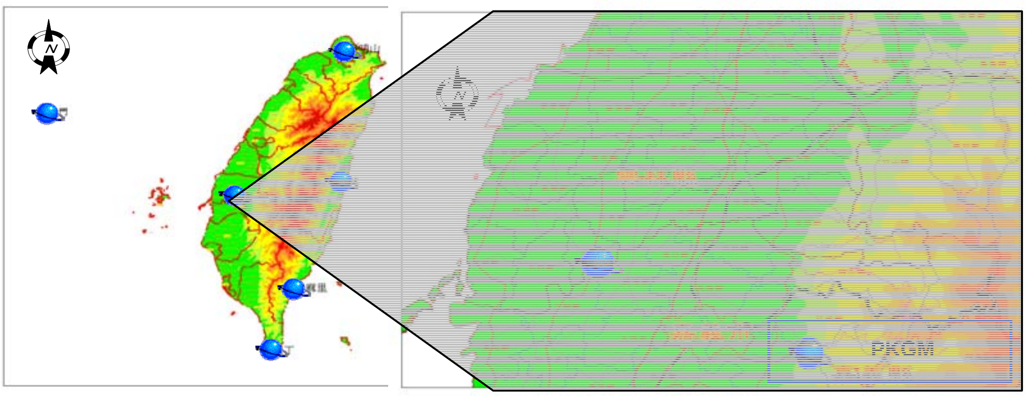

Fig. 2 Location of the test site (PKGM)

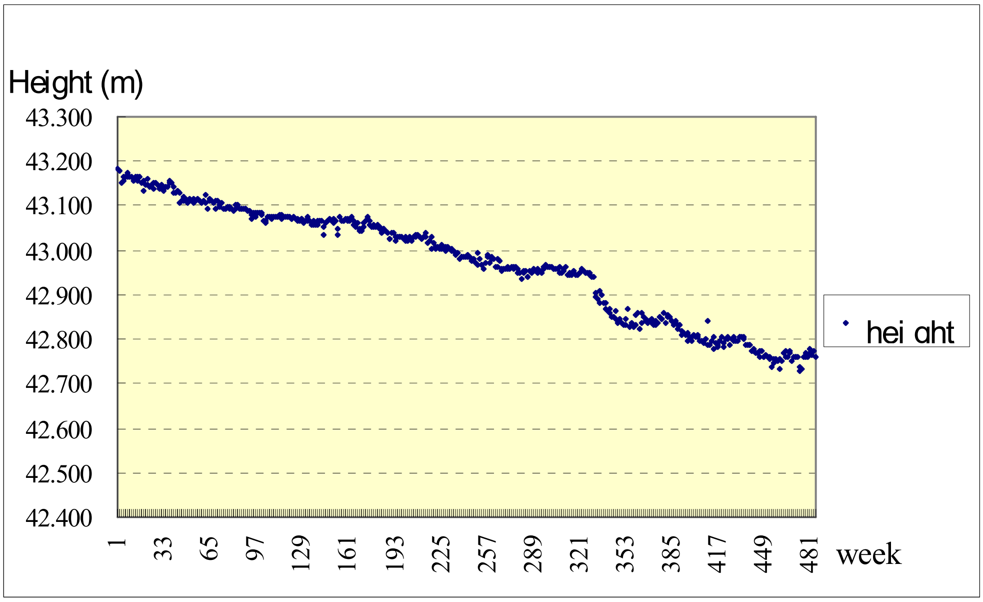

Fig. 3 Weekly height solutions observed at PKGM from 1995 to 2004

Since the operation of ANN model needs more epochs of data, whereas the GFT model requires only 5 epochs of data, this study employed two different periods of data sets, i.e. 5 weeks of short-term data and 52 weeks of long-term data, as the inputs for the two operation models. As it is nature that RA model can be worked with short-term or long-term data set, the RA model was both applied and compared for their model outputs (see Fig. 4). The output value was designed as the height prediction of next coming epoch, estimated by the three selected models using either pre-5-week or pre-52-week data set. The estimation precision can then be presented with the root mean square error (RMS), using the measured heights as the standard to compare with those estimated from the models operated.

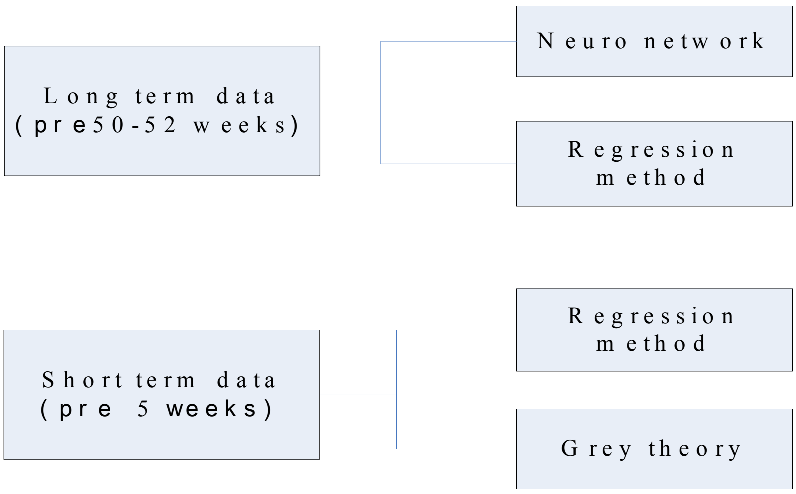

Fig. 4 Data sets and operation models applied

3.1 Long-term Data Tests

To carry on ANN operation with the long-term data set, a software package of Alyuda NeuroIntelligence Version 2.1 was adopted by the study (Alyuda Research Inc. 2003). The training samples, testing samples and verifying samples are randomly made (see as Fig. 5), and the optimum number of the hidden layer in use can also be automatically determined by the software (see as Fig. 6).

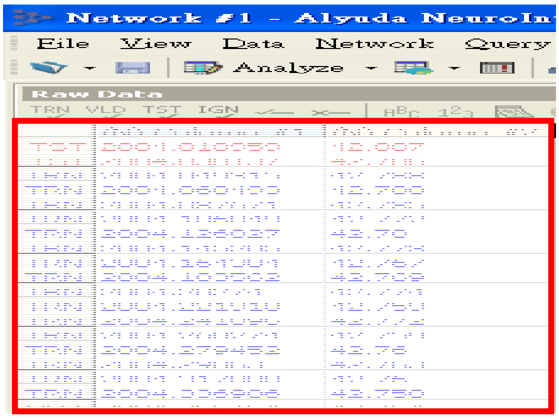

Fig. 5 Sample data used by ANN

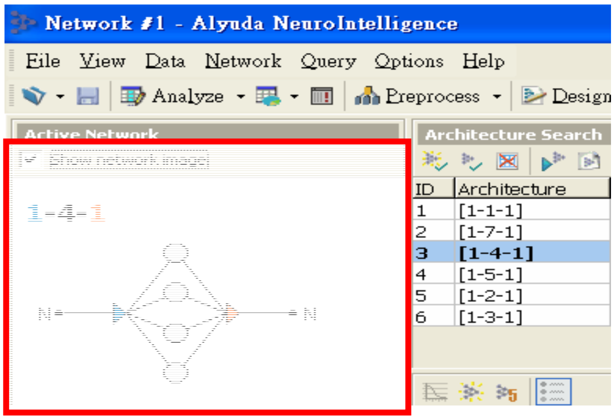

Fig. 6 Hidden layers used by ANN

In training process, seven kinds of training algorithm can be selected (see Fig. 7). The default option, i.e. a quick propagation algorithm with the coefficient of 1.75 and the learning rate of 0.1, was practically applied by this study. When the training process is carried out, the ANN testing network can then be formed (see Fig. 8).

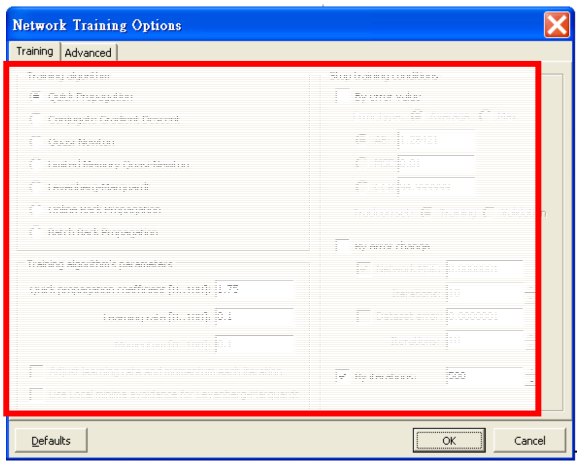

Fig. 7 Trainning algorithms for ANN

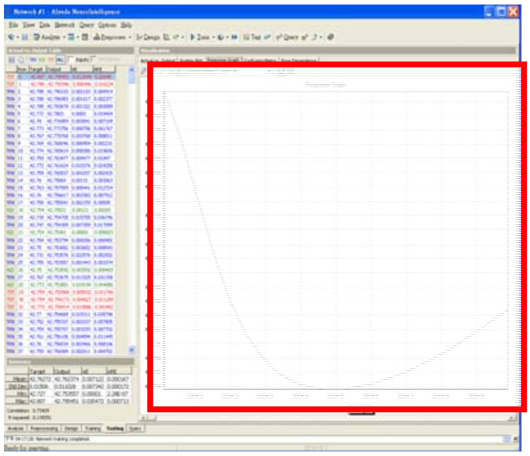

Fig. 8 Testing network used by ANN

The RMS errors of the height predictions based on ANN and RA models with the long-term data sets were estimated for 12 check epochs in a year (roughly one epoch per month). The average estimation error in each year and the overall average error as well as the standard deviation over the entire test period are listed in Tab. 1 and shown in Fig. 9.

Tab. 1 RMS error of height estimation based on long-term data

Year of Data	ANN model (cm)	RA model (cm)
1996	0.8	1.0
1997	1.5	0.8
1998	1.2	1.0
1999	0.7	0.8
2000	1.1	1.2
2001	0.7	0.8
2002	2.2	3.7
2003	0.8	1.7
2004	1.3	1.8
Average	1.1	1.4
Standard Deviation	0.5	0.9

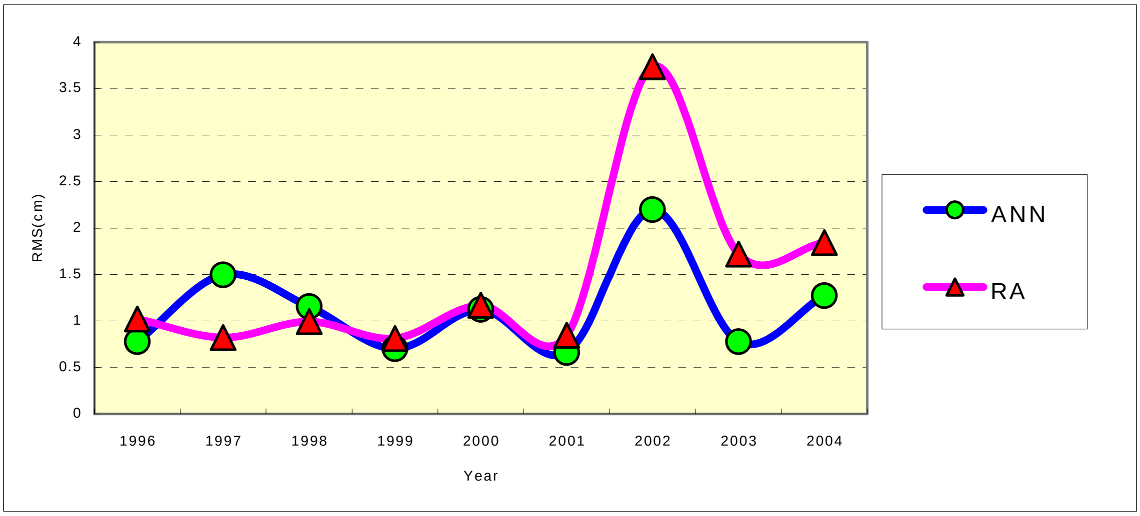

Fig. 9 Fitness errors based on long-term data testing

It can be seen in Tab.1 and Fig. 9 that the ANN model using pre-52 weekly solutions to estimate a series of heights provides the RMS error between 0.7 cm and 2.2 cm. The average RMS error and the standard deviation over the entire test period are 1.1 cm and 0.5 cm, respectively. Comparatively, the simple type of RA model estimates a slightly higher of error with a variation range of 0.8-3.7 cm and an average RMS of 1.4 cm associated with a standard deviation of 0.9 cm. In brief, the fitness of height estimation based on the ANN model shows a better performance, i.e. 27% in average, than that of predicted using RA model.

3.2 Short-term Data Tests

The heights estimated using GFT and RA models were also carried out for 12 check epochs in a year based on the short-term data sets. The fitness indications mainly relied on the average RMS error are listed in Tab. 2 and shown in Fig. 10.

Tab. 2 RMS error of height estimation based on short-term data

Year of Data	GFT model (cm)	RA model (cm)
1996	1.0	0.7
1997	0.9	0.8
1998	1.7	1.5
1999	0.9	0.9
2000	0.9	1.0
2001	0.6	0.6
2002	2.0	1.6
2003	1.8	1.6
2004	1.1	1.1
Average	1.2	1.1
Standard Deviation	0.5	0.4

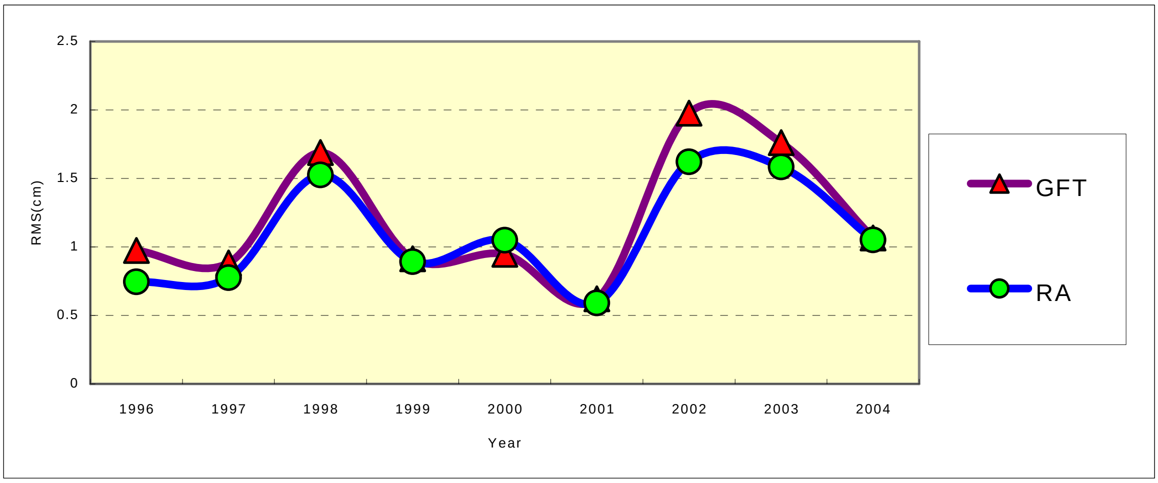

Fig. 10 Fitness error based on short-term data testing

It is found in Tab.2 and Fig. 10 that the simple type of RA model using short-term of pre-5 weekly GPS solutions provides a slightly better of fitness indication, where the overall average RMS error is 1.1 cm. This level of the estimation error suggests that the height fitness using RA or GFT model with short-term data can be equivalent to the ANN model with long-term data collected at the significant land subsidence area.

4. CONCLUSIONS AND SUGGESTIONS

In this paper, the application of using some selected models to estimate the height variations of a GPS monitoring station, as the prediction of land subsidence, has been investigated. The ANN model tested with 52 epochs of weekly solution in the data series indicated a height forecasting error of 1.1 cm, which is nearly equivalent to the precision of the first-order GPS control survey. Moreover, the fitness analysis also showed a consistent level of estimation error occurred by using a simple type of RA model with a shorter term, i.e. 5 weeks, of solution series. However, since the height variation caused by the land subsidence is a comprehensive reflection of various natural factors, such as the underground water level, surface rainfall and geological condition etc., it is necessary to collect more relevant information and to develop a more effective artificial intelligence method to accurately forecast the height variation of the monitoring site located in the land subsidence area.

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