Research on Satellite Orbit Prediction Based on Neural Network Algorithm

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ABSTRACT
Satellite orbits predictions is a significant research problem for collision avoidance in space area. However, current prediction methods for satellite orbits are not accurate enough because of the lack of information such as space environment condition. The traditional methods tend to construct a perturbation model. Because of the intrinsic low accuracy of the perturbation model, the prediction accuracy of the low-order analytical solution is relatively low. While the high-order analytical solution is extremely complex, it results in low computational efficiency and even no solution. This paper presents a satellite orbit prediction method based on neural network algorithm, which discovers the orbital variation law by training historical TLE data to predict satellite orbit. The experiment results show that the proposed algorithm is feasible.

CCS Concepts
• **Applied computing → Avionics**

Keywords

Satellite orbit; TLE data; Neural network; Algorithm

1. INTRODUCTION
At present, the satellite orbit is mainly predicted by the classical mechanical model. Perturbation have a great impact on satellite orbits, especially low-orbit satellites. Therefore, the traditional methods have defined the perturbation models, including the Atmospheric Resistance Model, the Earth's Non-spherical Gravity, and the Solar Radiation with received momentum. Because the accuracy of the perturbation model is not high and the parameters introduced above bring errors to the traditional method, the prediction accuracy of the low-order analytical solution is relatively low, and the process of the high-order analytical solution is extremely complex, resulting in low computational efficiency or even no solution.

TLE (Two-Line Elements) provided by NORAD combined with analytical models to make the orbit prediction is the mainstream method of satellite orbit prediction. Correlation model have high prediction accuracy. NORAD 's TLE needs to be calculated in the Simplified General Perturbation Version 4 (SGP4) Analytical Model. SGP4 is suitable for satellites with orbital periods of less than 225 minutes in near-Earth space [7].

Nowadays, the research on the accuracy of satellite orbit prediction focuses on the initial value of TLE and the optimization of each perturbation model. Although the traditional method is relatively mature, the accuracy and the efficiency of satellite orbit prediction needs to be improved. At first, the existing model considering the perturbation is an idealized model, which is very different from the real problem. Secondly, when predicting the satellite orbits belong to other country, it is difficult to obtain satellite orbit data, resulting in not timely corrected track. In the long-term orbit forecast, the model has error divergence.

In this paper, a neural network-based orbit prediction algorithm is proposed. The historical TLE data of the satellite is used as the learning sample of the neural network. Through the study of a large amount of data, the law of satellite orbit operation is obtained, and the satellite orbit is predicted.

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2. SATELLITE ORBIT DATA

2.1 Core track element description

According to the TLE data, the core data of the satellite orbit includes six integral constants, namely six elements of the Kepler orbit, including the semi-major orbit axis *a*; the orbital eccentricity *e*; the angle between the orbital plane of the satellite and the equatorial plane *i*; Equatorial longitude $\mathbf{\Omega}$; satellite orbital ascending node N (from the vernal equinox) ; Orbital perigee polar angle $\boldsymbol{\omega}$;Satellite near-site moment ξ.

After determining the number of satellite's orbit, the spatial position of a satellite can be determined at any one time. Usually, the TLE data issued by US international Global Earth Observation Network (SSN) is used as the satellite orbit data. It includes the orbital eccentricity *e*; the angle between the orbital plane of the satellite and the equatorial plane ***i***; Equatorial longitude $\mathbf{\Omega}$;the perigee polar angle $\boldsymbol{\omega}$. In addition, the angle of the ground angle $\mathbf{M_0}$ and the average motion $\mathbf{n_0}$ are also provided. These two parameters can be used to derive the satellite near-site moment $\boldsymbol{\xi}$ and the track half-axis a in the Kepler orbital parameter. Besides the six elements of the above-described six parameters ***e***, *i*, $\mathbf{\Omega}$, $\boldsymbol{\omega}$, $\mathbf{M_0}$, $\mathbf{n_0}$, also referred to two rows TLE track.

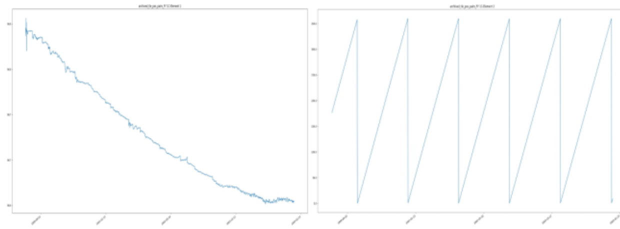
SSN publish one satellite orbit TLE data record for each satellite every day. With time T changing, two lines of rails TLE six elements is also changing. From the visual point of view, there may be some relationships between time and six tracks TLE. The physical meanings of the six elements of the TLE orbit are detailed in the table below. The orbit prediction with neural networks will use the following six elements in table1.

Table 1. Six core elements in TLE data

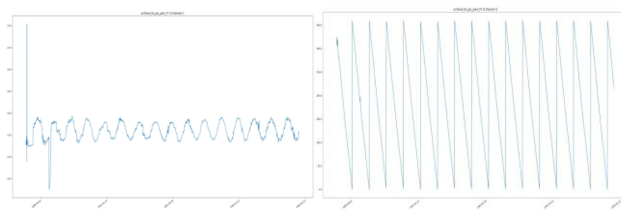
Six elements of orbit	Symbolic representation	Range	Remarks
Orbital inclination (degrees)	i	[0, 180)	Orbital inclination measures the tilt of an object's orbit around a celestial body.
Ascending node, right ascension (degrees)	$\mathbf{\Omega}$	[0, 360)	The ascending node (or north node) is where the orbiting object moves north through the plane of reference, and the descending node (or south node) is where it moves south through the plane.
Orbital eccentricity	e	[0, 1]	The orbital eccentricity of an astronomical object is a parameter that determines the amount by which its orbit around another body deviates from a perfect circle.
Perigee angular distance(degrees)	ω	[0, 360)	This is the opening angle of the perigee and the ascending node to the center of the earth.
Near point angle (degrees)	$\mathbf{M_0}$	[0, 360)	The angle of travel of an object on the track relative to the center point on the auxiliary circle
Average movement	n	Low- orbit satellites are larger than 24*60/255 (about 5.647)	The number of turns around the earth every day, the reciprocal of average movement is the cycle.

2.2 TLE source data analysis

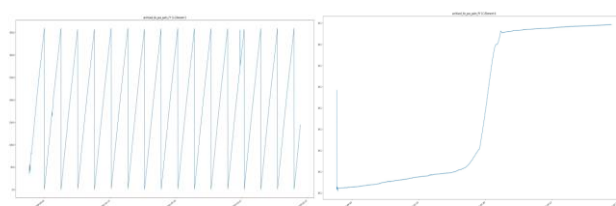
Using neural networks to predict the nature of the six elements of satellite orbit is to fit the curve of each element's value over time. To illustrate the variation of the six elements of satellite orbit, this section studies the TLE historical source data. The data used is the TLE of the meteorological satellite FY 1C from year 1999 to 2005. The six elements and time are extracted from the TLE data. We draw a time series of six elements, as shown below:



(a) Orbital inclination i (b) Ascending node Ω



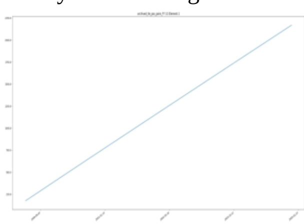
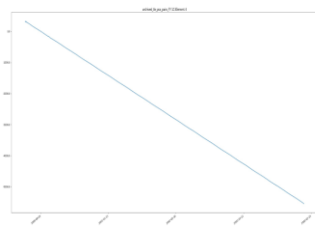
(c) Orbital eccentricity e (d) Perigee angular ω



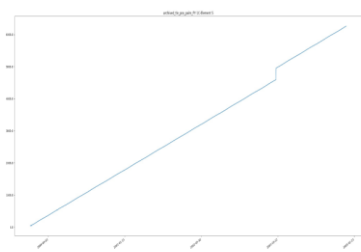
(e)Near angle M_0 (f) Average motion n

Figure 1. Timing variation of six elements of TLE orbit

From the figure, we can see that the range of variation of the first element orbital inclination *i* and the sixth element average movement *n* is very small, the orbital inclination angle changes about 0.2 degrees in the 7- year time span, and the average motion *n* varies within 1 day. Seen from (c) in Figure 1, the fluctuation range of the third feature orbital eccentricity *e* is from about 4000 to 24,000, but is represented by its eccentricity, the range should be between 0-1, according to the instructions TLE track acquired from TLE. Each data in this set should be placed after a decimal point, so that the change in *e* is within the range of 0-1, and its curve shows a wave shape. The curves of the three elements of the orbital inclination *i*, the average movement *n*, and the orbital eccentricity *e* tend to be continuous and smooth, and are suitable for fitting with a neural network. The second element of the TLE orbit $\mathbf{\Omega}$, the fourth element ω, and the fifth element $\mathbf{M_0}$ are showing a “serrated shape”, that is a non-continuous type. The degree at the angle Change to the maximum (minimum) value, suddenly reverse to the minimum (maximum) value, and restart to change in an approximately linear trend. Such non-continuous curves are not suitable for fitting with neural networks, and the data preprocessing is required. For example, a sinusoidal function can be used to transform a "sawtooth" discontinuous curve into a continuous sinusoidal continuous curve; or use stitching. Because the angle range is 0-360, we can shift the starting point of the curve that suddenly drops or rises up to the end of the previous curve. In this paper, the second method is used to preprocess the data of three “serrated” parameter elements. The processed curve is approximately continuous linear (as shown below) and can be directly trained using neural networks.

(a) Ascending node Ω (b) Perigee angular distance ω



(c) Near point angle M0

Figure 2. The trend of pretreatment after the ascending node of the six elements of the TLE orbit, Ascending node Ω, the perigee angular distance ω, and the near-point angle $\mathbf{M_0}$

3. FORECASTING TRACK

3.1 Neural network algorithm selection

Rumelhart [1] proposed neural network cycle (Recurrent neural network s, RNNs) in 1986. The main goal of RNNs is to process serialized data. The traditional neural network structure is a hierarchical structure of input layer, hidden layer and output layer. Each layer has multiple neural nodes. The neural nodes in the same layer are connectionless, and the layers are fully linked. When the current period information is relatively close to the current task distance, the previous information can be well preserved and transmitted to the current task through the sequence structure of the cyclic neural network. However, when the current preliminary information required for the task is too far, RNNs cannot learn this preliminary information, this is disappearing gradient problem. That is, the following nodes have a lower perceived power for the previous nodes.

In the long-term dependence, RNN cannot learn well. Hochreiter and Schmidhuber proposed a long-term and short-term memory model in 1997 [3]. Long-term and short-term memory networks known as "LSTM" are a special kind of RNN, which can deal with long-term dependency. LSTM is clearly designed to avoid long-term dependencies and to remember information for a long time without deliberate learning.

All recurrent neural networks have the form of a series of repetitive neural network modules. In standard RNNs, this module repeated is a very simple structure, such as a single *tanh* layer. The schematic diagram is shown as 2:

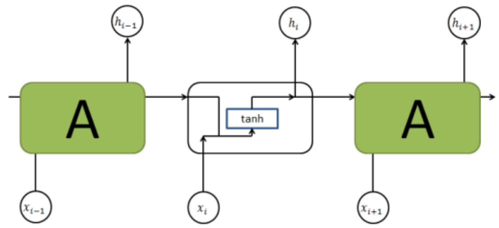


Figure 3. Standard cyclic neural network repeating module

LSTM is also a chain structure, but repeating modules have different structural designs. Compared to the simple *tanh* of the computational unit of traditional RNNs, there are four layers of neural network layers in the LSTM computing unit, which interact in a special way, as shown in Figure 3:

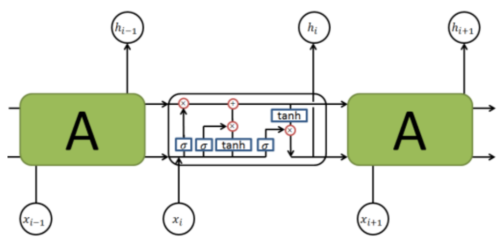


Figure 4. LSTM Repeat Module

The core of LSTM is the state of the cell, which runs through the horizontal direction. LSTM uses a well-designed door structure to make changes in cell status. A gate is a way to make information choices pass. The gate contains a sigmoid neural network layer and a Point wise multiplication operation. LSTM has three doors to protect and control the state of the cell, namely: input gate, forgetting gate, the output of the gate. The forward propagation of LSTM is calculated as follows:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right)$$
$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$
$$\tilde{C}_t = tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$
$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$
$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$
$$h_t = o_t * \tanh(C_t)$$

In the above formula, $f_t$means forgetting gate, i_t indicates the input gate, $\tilde{C}_t$ representing candidate values, C_t representing a new state of the cell, o_t indicates the output gate, o_t indicates the output value, x_t indicates the current input value.

3.2 Orbital element learning algorithm based on neural network

The neural network algorithms for satellite orbit prediction is divided into two parts: 1) forecasting the core elements of TLE orbit data; 2) forecasting satellite position and velocity. The prediction of the core elements of the satellite is to forecast the six elements of the TLE orbit. By training the historical TLE data, the prediction model of the trend of the six elements over time is obtained. The six forecasting elements of the orbit after 1 day, 3 days, 5 days and 10 days. The forecasting result of the six elements of TLE can generate complete TLE data in turn. Forecasting the position and velocity of the satellite means that the prediction model is formed by training the correspondence between the six elements of the TLE and the speed of the satellite position. During the forecasting process, by providing the six elements of the TLE of the satellite, the position and the speed of the satellite at any time can be obtained.

LSTM algorithm based on neural networks is suitable for processing time series data, therefore we use the present cycle of the neural network LSTM to make TLE satellite orbit prediction, combined with characteristic data using linear regression fit of the data portion in the prediction process. Our method is based on the characteristics of six elements of TLE data and its physical meaning, and we adding the TLE data to obtain timestamp T and the time interval D between adjacent TLE.

Data are added to construct a TLE forecast eight for TLE data prediction. The elements are as follows:

$$\text{var} = \{\text{e, i, } \Omega, \ \omega, \mathbf{M_0}, \mathbf{n_0}, \text{T, D}\}$$

The first six elements of var is two rows of six elements TLE orbital data. Before training the prediction model, the raw TLE data needs to be pre-processed to accommodate the input of the LSTM model. According to the previous definition, the TLE six orbital data is corresponding to the time stamp data T based on track TLE. Then, the time interval D between adjacent data is calculated for the time-ordered orbit data, thereby constructing the eight elements of the TLE orbit prediction.

Because of the complexity of the neural network training a number of parameters, this paper respectively on the six elements of the track for training and forecasting. According to the time series analysis of the six elements of TLE orbit in Section 2.2, the orbital inclination *i*, the orbital eccentricity *e* and the average movement *n* can be directly trained by the neural network. This section is based on the three elements respectively. Figure 5 shows the structure of the LSTM prediction algorithm.

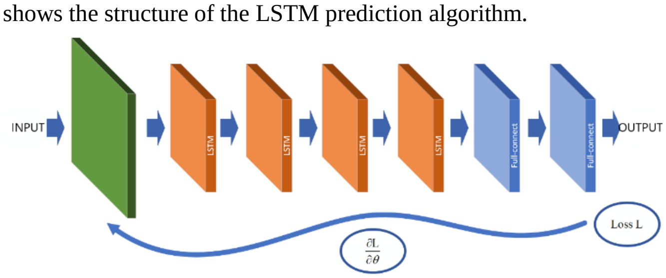


Figure 5. Neural network model for predicting orbital parameter elements based on LSTM

The LSTM- based prediction model consists of four parts, as shown in the figure above:

(1) Input layer: Eight element data of TLE orbit prediction.

(2) LSTM layer: Obtain high-dimensional features of the eight-element data of TLE orbit prediction.

(3) Full-connect layer: Integrate the acquired high-dimensional features.

(4) Output layer: Calculate the predicted value of the target element and outputs it.

Take the prediction model of the orbital inclination *i* as an example. We take historical continuous data in N days as input x, the value corresponding to the first N+1pieces TLE orbit inclination *i* of the data as the output data y to construct prediction orbital elements. During the training of the model, the input layer of the model accepts the input data x. Followed by LSTM layer, we use it to learn the high dimensional feature data of the N TLE longer time span. Then fully connected layers integrate the acquired high-dimensional features, and give regression vectors to get R^*. Finally, the regression layer at the output layer make a linear combination to get the corresponding feature prediction $\tilde{y}$.

In this paper, we use RMSE (Root Mean Squared Error) as a loss function. The loss function of the model is as follows:

$$J(\theta) = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(y_i - \tilde{y}_i)^2}$$

Where θ represents the weight parameter in the neural network model, and m is the number of samples predicted during the training. In the training process, iteratively update the parameter θ by the gradient descent method to complete the minimization. The goal is to obtain a more accurate prediction model of the orbital parameters based on LSTM.

For the other three elements of the orbit: the ascending node Ω, Near-point angular distance ω and near-point angle M_0 According to the changes of section 2.2 of its data, this paper assume that these three elements is approximately linear with time in a short time span. Therefore, our prediction model uses the linear regression (Linear Regression) algorithm to predict for these three elements. For example, In this paper, the time stamp T of the eight elements of the orbit prediction and the ascension point of the ascension point Ω are respectively used as the model input, and the output value is used to evaluate the accuracy of the model. The forecast problem can be defined as:

Given variable $\{(t_1, y_1), (t_2, y_2), \dots, (t_m, y_m)\}$,among them $t \in R^n, y \in R$. The goal is to find the most suitable function F(t): $f: R^n \to R$.

Since y and t are approximately linear, the relationship can be expressed as:

$$f(w_1, \dots, w_n, b) = y = w \cdot t + b + \varepsilon$$

Where w represents the coefficient and b represents the intercept. In order to find the best function in the prediction algorithm based on linear regression , the model prediction value is also used RMSE as the loss function between predictive value $\tilde{y}$ and the true value y used as an evaluation index for predicting the degree of good or bad.

$$J(\theta) = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(y_i - \tilde{y}_i)^2}$$

Where θ represents the weight parameter in the neural network model. During the training process, the parameter θ is iteratively updated by the gradient descent method, so that we get the smallest value for J(θ).

In summary, according to the time series variation characteristics of the six element parameters of TLE orbit, a combination of LSTM neural network and linear regression is used to predict the TLE orbit. The description is shown in the following figure:

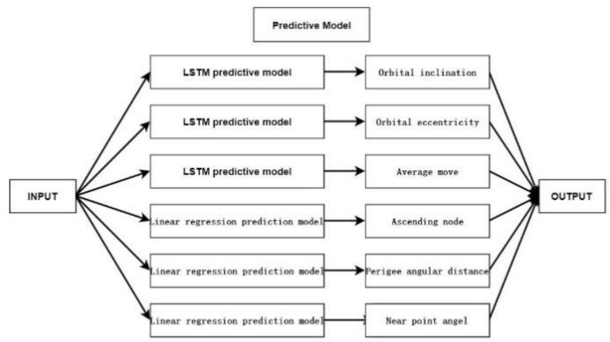


Figure 6. Schematic diagram of six elements of TLE orbit based on LSTM neural network and linear regression

4. PRELIMINARY RESULTS

4.1 Experimental Data

The object satellite with data in our experiments is the satellite IRIDIUM. The IRIDIUM is composed of 66 operational satellites around the earth. The Iridium mobile communication system is the first generation of satellite mobile communication constellation system proposed by the United States in 1987. The mass of each satellite is about 670 kilograms and the power is 1200 watts. It adopts a three-axis stable structure, and the channel of each satellite is 3480. Service life is 5-8 years. This system originally planned 77 communication satellites, so it was named after the atomic order of 77.

We collected historical TLE data for the satellite debris fragment IRIDIUM 118, from 1982 to 2004, a total of 16818. We randomly select 80% of the data set as the training set and the remaining 20% of the data as the prediction set, as shown in the following table.

Table 2. Experimental data description

Satellite debris TLE	Total amount of data	Training set (80%)	Test set (20%)
IRIDIUM 118	16818	13455	3365

The experimental environments configured with an NVIDIA GeForce GTX1080Ti GPU with 11GB of memory, a core frequency of 1481-1582MHz, and an operating system of 64 -bit Ubuntu 18.04. The experiment is based on the Keras library under the TensorFlow framework and the Sklearn machine learning library.

4.2 Forecasting TLE Orbital Elements Based on Neural Network

This section gives the process and results of predicting TLE orbits
based on neural networks. After extracting the six elements of the satellite's orbit from the original TLE data, the pre-processing is training data and test data, and the training data is used for training to obtain the neural network prediction model, and then verified on the test data set. The parameters of the LSTM neural network training process are adjusted as shown in the following table:

Table 3. Parameters of the LSTM neural network training process

Serial number	Hyperparameter	Meaning	Defaults
1	Batchsize	The size of the data foreach batch feed into LSTM	4
2	Input time steps (sequence length)	Expanded LSTM block nu mber. i.e. the first N values with predicted values of the first N + 1	5
3	Learning rate learning rate	Step size of back propagation during training	0.01 (decay=0.0001)
4	Optimization Strategy Optimizer	Gradient update rule	Adam
5	Training peri od Epoch	The number of times the model is trained. When the loss function tends to be stable, increasing the epoch does not improve the effect of the model.	100
6	Loss function loss	The degree of inconsistency between the predicted value f(x) of the estimated model and the true value Y	Mse
7	Activation function	Nonlinear module	Relu
8	Network structure	Number of LSTM layers, number of dense layers, number of neurons in dense layer	LSTM 5 layers Dense: 3 layers

The experimental results show the minimum value of the root mean square error RMSE of LSTM and linear regression (see Table 3 below), which is the optimal result during the whole training process. The smaller the RMSE value, the more accurate the prediction of the neural network model and the linear regression model. In the training process of the neural model, in order to make the model more effectively, this paper firstly processes the data according to the respective characteristics of the six elements of TLE orbital data. The loss values during the training process for different orbital element models are shown in the following table:

Table 4. Six element prediction model for TLE orbit

Serial number	Parameter	RMSE optimal value
1	Orbital inclination i	0.21
2	Ascending node Ω	1.1151e-6
3	Orbital eccentricity e	1.3925e-8
4	Perigee angular distance ω	0.1492
5	Near point M 0	0.170 8
6	Average movement n	3.7867e-4

1) Comparison of the accuracy of the six-factor prediction results

This paper uses the 20 TLE data in 15 days to test the model proposed in this paper. The experimental results are shown in the following table:

Table 5. Predicted result of the TLE element

	Orbital inclination	Ascending node	Orbital eccentricity	Perigee angular distance	Near point	Average motion
1	0.188519	0.000765	9.43E-05	0.302443	0.307218	0.273772
2	0.189319	0.000981	8.70E-05	0.411762	0.418171	0.273774
3	0.189219	0.000985	8.71E-05	0.345492	0.353944	0.273775
4	0.189319	0.001026	8.74E-05	0.207561	0.220681	0.273775
5	0.189319	0.001146	8.65E-05	0.11521	0.133307	0.273775
6	0.189319	0.001159	8.65E-05	0.1036	0.121587	0.273775
7	0.189619	0.001579	7.51E-05	0.254349	0.277013	0.273773
8	0.189619	0.001711	7.25E-05	0.134387	0.163519	0.273773
9	0.189819	0.002053	6.67E-05	0.123557	0.158856	0.273775
10	0.189919	0.002264	6.52E-05	0.014775	0.056851	0.273777
11	0.189919	0.002402	6.39E-05	0.040685	0.005615	0.273778
12	0.189919	0.002505	6.20E-05	0.044155	0.005188	0.273779
13	0.190419	0.002938	6.11E-05	0.166717	0.109806	0.273782
14	0.190519	0.003358	5.72E-05	0.217968	0.15308	0.273783
15	0.190619	0.003691	5.14E-05	0.259429	0.186474	0.273782
16	0.190619	0.003924	4.65E-05	0.33809	0.256768	0.273783
17	0.190919	0.004743	3.86E-05	0.295741	0.206841	0.273783
18	0.191019	0.005085	3.54E-05	0.358772	0.261105	0.273783
19	0.190919	0.005114	3.15E-05	0.392963	0.290671	0.273783
20	0.191019	0.005318	2.80E-05	0.414033	0.307898	0.273783

Different elements have different ranges of values. According to the comparison between the six-element data of TLE orbit and the prediction error of the model, the six-element prediction algorithm of TLE orbit proposed in this paper is described (six elements are described). The six-element prediction algorithm of TLE orbit proposed in this paper has higher prediction accuracy on orbital eccentricity, ascending node red longitude and average motion elements.

2) Obtain the six elements of TLE according to the forecast and evaluate the accuracy of the position

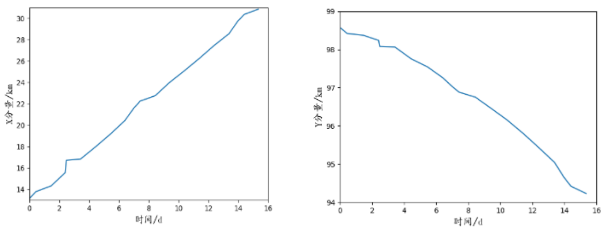
Using the six elements of the TLE orbit obtained by the model prediction, the prediction information of the position of the spacecraft is obtained. The results of the comparison between the predicted results of the spacecraft position and the real data are shown in the following table:

Table 6. Predicted position of the spacecraft

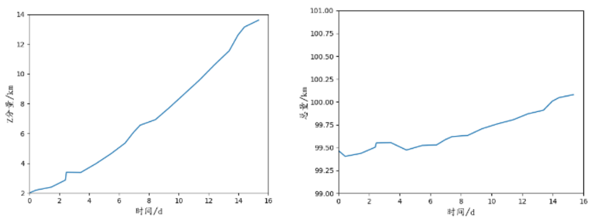
	Δx(KM)	ΔY(KM)	ΔZ(KM)	Total (KM)
1	13.14575	98.57439	2.00185	99.46722
2	13.78685	98.41967	2.192267	99.4048
3	14.32141	98.3712	2.390918	99.43698
4	15.56539	98.23831	2.864089	99.50503
5	16.7174	98.07934	3.393236	99.55171
6	16.82597	98.0648	3.368956	99.55485
7	17.98191	97.75486	3.959726	99.47382
8	19.20061	97.54386	4.633644	99.52356
9	20.43904	97.26149	5.347082	99.52961
10	21.56356	97.03486	6.090021	99.58835
11	22.24872	96.88281	6.555485	99.62058
12	22.75913	96.75177	6.925718	99.63357
13	23.98343	96.4697	7.744851	99.70753
14	25.10303	96.16015	8.678308	99.76096
15	26.27826	95.80256	9.615672	99.8055
16	27.43492	95.44274	10.58072	99.86963
17	28.55956	95.04053	11.55436	99.90923
18	29.72234	94.6545	12.60294	100.0086
19	30.35768	94.41909	13.14837	100.0471
20	30.84974	94.22887	13.60809	100.0798

For the 15-day time span, the prediction model proposed in this paper has an error of 30km on the x-axis, 94km on the y-axis, 13km on the z-axis, and a total error of 100km.

In order to visualize the trend of the prediction results on the X-axis, Y-axis, and Z-axis with respect to time, select 0-16 days on the time axis. We plot the variation of the error and the overall error under each coordinate axis, as shown below:



(a) the variation trend on X-axis (b) the variation trend on X-axis



(c)the variation trend on Z-axis (d) the overall change

Figure 7. The variation trend of predicted position on X-axis, Y-axis and Z-axis. And the overall change of the predicted position

As time increases, the predicted position shows an upward trend in overall error, but the increase is relatively stable, and the growth scale is small. Predicted higher accuracy on the X and Z axes.

5. CONCLUSION

This paper first introduces the LSTM algorithm and TLE data, expounds the principle of LSTM algorithm and the physical meaning of each parameter of TLT orbit, and draws the curve of six elements with respect to time. The curves of the three elements of orbital inclination, average motion and orbital eccentricity are continuous and smooth, which is suitable for direct fitting with neural networks. The trend of the ascending node Ω, near-point angular distance ω and near-point angleM_0 are all "Sawtooth". According to the characteristics of its shape, we use the regression prediction method.

Based on the above prediction model, the six elements of TLE orbit are obtained. In the experimental verification, the RMSE training error of the ascending node, the orbital eccentricity and the average motion is ideal, and it is too sensitive to the abnormal data points in the orbital inclination and other factors. Predictive models on elements such as orbital dips need to be further improved. Based on the six-element prediction data, the predicted position of the satellite is obtained, and the predicted position error is within the acceptable range, and the change of the predicted position error is relatively stable against the progress of time. In the following, we will consider decreasing the error of the three factors of orbital inclination, perigee angular distance and perigee angular distance. At the same time, we will increase the size of the training set and use different time series processing algorithms to carry out further work to improve the prediction accuracy.

6. REFERENCES

[1] Rumelhart, David E, Hinton. Learning representations by back-propagating errors [J]. *Nature*, 1986, 323(6088): 533-536.

[2] Hochreiter S. *Untersuchungen zu dynamischen neuronalen Netzen*[C]. Master's Thesis, Institut Fur Informatik, TechnischeUniversitat, Munchen. 1991.

[3] Hochreiter S, Schmidhuber J.*Long short-term memory*[M]. Supervised Sequence Labelling with Recurrent Neural Networks. Springer Berlin Heidelberg, 1997: 1735-1780.

[4] F.A.Gers, J.Schmidhuber Recurrent Nets that Time and Count [C]*IEEE -Inns- Enns International Joint Conference on Neural Networks*. IEEE, 2000:189-194 vol.3.

[5] Cho K, Van Merrienboer B, Gulcehre C, et al. Learning Phrase Representations using RNN Encoder-Decoder for Statistical Machine Translation[J]. *Computer Science*, 2014.

[6] Yan Ruidong , Wang Ronglan , Liu Siqing , Liu Wei , Gong Jiancun . Covariance calculation and application of space target collision warning. *Chinese Journal of Space Science*, 2014, 34(4): 441-448.

[7] H. Bolandi, MH Ashtari Larki , SH Sedighy , MS Zeighami , and M. Esmailzadeh . Estimation of Simplified General Perturbations model 4 orbital elements from global positioning system data by invasive weed optimization algorithm. *Proceedings of the Institution of Mechanical Engineers, Part G: Journal of Aerospace Engineering 229*, No. 8 (2015): 1384-1394.