Use the τ-Steps Ahead Predicting to Discover the Trading Signal

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Abstract

In the past decade, many researchers used the artificial intelligence, chaos theory and time series to identify the predictive function. Or according to the fractal geometry to analyze the time series, expanded the time scale, because the fractal surfaces retained the self-similarity, let τ-steps ahead was predicable. They had a good predictive results, let the τ-steps ahead prediction error could be controlled in small range. But, they have had a common problem: could not identify the limit of prediction. In this paper, we based on the fractal geometry adopted the Genetic Programming (GP) and multi-acquiring method to get τ-steps ahead predictive function. And the predictive error (SSE) was only 246, when expanded our model to τ-steps ahead predicting the predictive precision is as same as the one-step ahead. Then we accord the error distributions to decide at the 95%, 75%, 50% and 25% confidence, relied on these trading prices to get the benefit. The high confidence strategy could bring the high trading times and brought high EOR. From the experimental results we found at the 95% confidence the EOR could reach 65%.

Keywords: τ -steps ahead predicting, chaos, self-similarity, fractal, genetic programming

1. Introduction

Kumar and Tan[7] investigated the performance of predictability by statistic method and artificial intelligence, found the artificial intelligence had high precision. But, they also weaved embedding theory into ANN to increase the predictive precision. At same time many studies (Eric [1], Iba [4], Kaboudan [5][6], Tan [12])had incorporated the chaotic component of a time series to analyze the non-linear properties of the stock market data. They also had a good predictive precision.

But for long term prediction, another prediction method (Tokinaga[11][13]) the fractal geometry of the time series was used to expand the time scale, and because the fractal surfaces had the retaining self-similarity. It could treats an estimation method for fractal surfaces to demonstrate the ability of the prediction method for various fractal dimensions by showing that the one-step-ahead prediction error was very small, and the τ-step-ahead prediction error also could be controlled in small range.

Therefore, from above studies we can find many researchers based on the chaotic trajectory run τ-steps ahead predicting, and the chaos is used to identify the predictive function for non-random time series. But, the τ-steps ahead predicting can easily cumulate the predictive error; let the prediction become more difficult. And if we want to increase the benefit on the stock market, how to acquire the trading signal from the chaotic trajectory and decrease predictive error becomes an important problem.

2. Methodology:

Here we according to the fractal have the self-similarity effect decompose the fractal to some partial fractals and use the GP to learn every partial fractal's predicting function. Then, we can integrate all partial fractals' predicting values, to generate the one-day to τ-day predicting values, and help us find the short-period in there. Based on this information we can discover a good timing to earn the maximum benefit. The detail process is as following:

Phase 0: Decompose a Chaotic time series to τ Partial Fractals' time series

The embedding theory is used to find the optimal delay time τ, here we used algorithm is developed by Gautama et., al [2], and then according to the τ value decompose a chaotic time series to τ partial fractals' time series as formula (1).

$$X_{t+1} = f_1(x_t, x_{t-\tau}, x_{t-2\tau}, \dots, x_{t-(\tau)\tau})$$
$$X_{(t+1)+1} = f_2(x_{(t+1)}, x_{(t+1)-\tau}, x_{(t+1)-2\tau}, \dots, x_{(t+\tau-1)-(\tau)\tau})$$
$$\vdots$$
$$X_{(t+\tau-1)+1} = f_\tau(x_{(t+\tau-1)}, x_{(t+\tau-1)-\tau}, x_{(t+\tau-1)-2\tau}, \dots, x_{(t+\tau-1)-(\tau)\tau}) \quad \text{….. (1)}$$

Phase 1: the Multi-Acquiring and Additional Fractal Algorithm

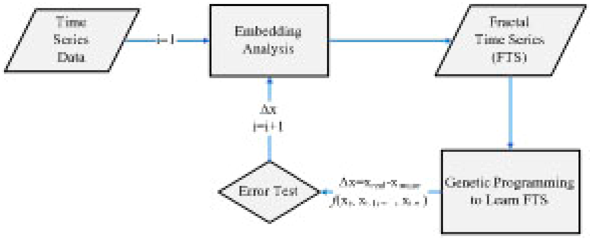

Fig. 1: Multi-acquiring and additional fractal algorithm

1st **step:** The genetic programming (GP) and sliding window (window length is τ) are used to learn history data and create the forecasting function. Then, integrate these predictive values from all partial fractals' predictive function as xmajor and the xreal is the raw time series.

2nd **step:** Analyze the predictive error and generate the predictive function

Follows the Eq. 2, calculates the error time series and here we use the Ljung-Box test to test the predictive error time series. If the result point out the predictive error time series is the randomness, we will stop the learning process. The other is the error time series has to training by GP to construct the residuary forecasting function and the final predictive value is the fmajor add f like formula (2). Goto step 1.

$$\Delta x = x_{real} - x_{major}$$

$$\Delta x_{t+1} = f_{\Delta}(\Delta x_t, \Delta x_{t-1}, \Delta x_{t-2}, ..., \Delta x_{t-\tau'}) \quad ..... (2)$$

$$x_{t+1} = f_{major}(x_t, x_{t-1}, x_{t-2}, ..., x_{t-\tau})$$

$$+ f_{\Delta}(\Delta x_t, \Delta x_{t-1}, \Delta x_{t-2}, ..., \Delta x_{t-\tau'})$$

Phase 2: Discover the trading signal

1st **step:** the τ-days' predicting prices are used to discover the short period's minimum price and maximum price.

2nd **Step:** if the short period is longer than τ-days, the sliding window is used to extend the predicting and the system continually monitoring the minimum price or maximum price. Here we have four cases:

Case 1: If the price continually increases, the maximum price also continually is replaced by new price.

Case 2: If the new predictive price starts decreasing from maximum price, then we can find the selling signal.

Case 3: If the price continually decreases, the minimum price also continually is replaced by new price.

Case 4: If the new predictive price starts increasing from minimum price, then we can find the buying signal.

3rd **step:** at case 2 and case 4, we are according to there own predicting error distribution to decide the trading price at the confidence on 95%, 75%, 50% and 25%. And calculate the benefit in this short period, and then we will cumulate all test period's benefits.

3. Experiment Results & Discussion

The Hon Hai Precision Ind. Co. is our target stock, the experimental data is from TSEC, and the period is from 01/10/2001 to 12/31/2003. The total data is 741, the top 590 is used to training and remainder 151 is for test. All data is the raw data.

Phase 0: generate the partial fractal time series

The Gautama et., al [2]'s algorithm was used to analyze the delay time, the delay time was 8(τ=8).

Phase 1: Use the multi-acquiring and additional fractal algorithm to increase the predictive ability

1st **step:** Collected all predictive values to build a new time series (x_{major}).

2nd **step:** calculated the residuary error(x), if the result of Ljung-Box test was not very agreeable that the error time series was not the randomness, went to the step 1 learning again. And the error time series was also used to training by GP to construct the residuary forecasting function(f). The SSE's result was shown on table 1 and the predicting error time series was also shown on Fig.2.

Table. 1: the Character of the sub-fractal's predictive error distribution and SSE

Fractal	Mean	Sigma	Skew	Kuro	SSE
P1	0.931	10.075	-0.372	5.14	82.826
P2	0.265	5.398	-0.845	5.307	44.24
P3	0.038	0.973	0.638	3.272	7.967
P4	0.741	10.744	-0.697	4.113	88.155
P5	0.113	1.299	-0.567	4.683	10.677
P6	0.918	3.87	0.296	6.054	32.619
P7	0.111	1.23	0.013	2.83	10.109
P8	0.022	1.329	-0.175	3.6	10.878
total					287.47

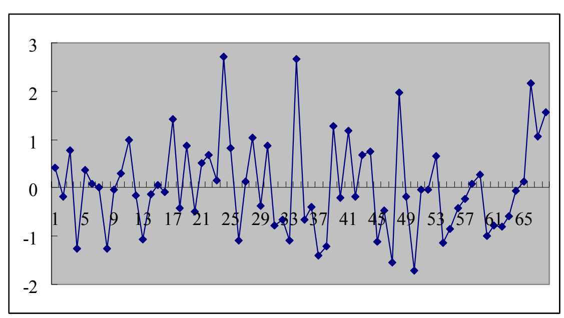

Fig. 2: our model's predictive error.

The above experimental results could evidence our model could clearly catch the vibration of stock's price.

Phase 2: Discover the trading signal

According to the predictive time series as Fig. 3, the system would along the discovering algorithm to find the selling signal and buying signal as shown on table 2. Then we depended on each sub-partial predictive error to get there owning error distribution, one of them was shown on Fig. 4. Use these error distributions to decide the confidence at 95%,, 75%, 50% and 25%. And relied on these trading prices to get the benefit were also shown on table 2. We could find that it did not like the one-day ahead predicting could not find the short period, the high confidence strategy could bring the high trading times and brought high EOR.

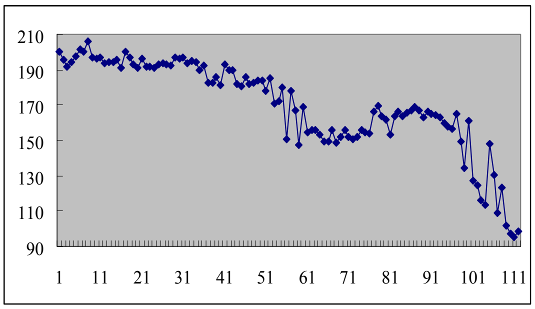

Fig. 3: The predictive time series, the x-axis means days and the y-axis means prices.

Table. 2: EOR vs. Confidence

	95%	75%	50%	25%
1	7.4	7.4	7.4	
2	4.9	4.9	4.9	
3	6.4	6.4	11.7	
4	15.3	11.7		
5	11.3			
6	0.5			
7	8.6			
Total	64.4	30.4	24.0	0

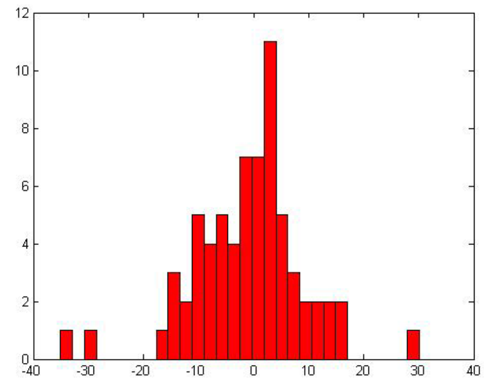

Fig. 4: P1's predictive error distribution. The x-axis means EOR and the y-axis means frequency.

4. Conclusions

In this study we had three experimental results: first, the τ-steps ahead predicting error was the same as one-step ahead. And the multi-acquiring and fractal trajectory method could pick up all meaningful information, let the residuary error was as the white noise. And because the distribution of predictive error liked the normal distribution, we could investigate the residuary error distribution to decide the trading price on 95% confidence. Second, we can run τ-steps ahead predicting process, let we had a chance to discover the short period. According to this short period, we could find the minimum price and the maximum price, these information were our trading signal. Third, we accord the error distributions to decide at the 95%, 75%, 50% and 25% confidence, and the trading process got the selling signal and buying signal. From the experimental results we found at the 95% confidence the EOR could reach 65%. The high confidence strategy could bring the high trading times and brought high EOR.

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