A Fractal Feature-Based Model for Predicting Financial Price Trends

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Abstract. The complexity and unpredictability of financial markets have been the focus of attention for investors and researchers. Traditional financial time series analysis methods have limitations in dealing with nonlinear and non-stationary data, while fractal theory, as a tool for studying complex systems, shows potential advantages in financial price trend forecasting. This study aims to investigate the effectiveness and application of fractal features in financial price trend forecasting. Firstly, the study reviews the basic concepts of fractal theory and resamples financial data based on fractal features, secondly, the study proposes a financial price trend prediction model incorporating fractal features and predicts future price trends by slipping the specified categorical voting rules. In addition, the study explores how to combine fractal features with traditional technical analysis tools and machine learning algorithms to improve the accuracy and robustness of the forecasts. Finally, empirical analyses are conducted with real data from financial markets, and the results show that fractal features can effectively reveal the non-linear patterns of price fluctuations and can effectively reveal the self-similarity characteristics of financial markets. We expect to provide a new perspective and tool for financial market analysis and investment decision-making to cope with the uncertainty and complexity of financial markets.

Keywords: fractal self-similarity; resampling; financial price trends

1 Introduction

The unpredictability of financial markets has been a focus of attention for investors and academics. The prediction of price trends is crucial for investment decisions as it is directly related to asset allocation, risk management and market efficiency[1]. However, traditional financial theories and models often struggle to accurately capture the complex dynamics of the market, especially in the face of extreme events and unconventional volatility.A Weron used a fractal approach to analyse financial time series, proposing the fractal market hypothesis and power laws on different time scales[2]. Marc Lamphiere Jonathan Blackledge and Derek Kearney developed indicators to predict future short-term behaviour based on the Fractal Market Hypothesis (FMH) using an alternative trend forecasting strategy based on the Intercontinental Exchange (ICE) data for the period 2005 to 2019[3]. Przemysław Juszczuk et al. experimentally investigated the use of similarity indicators to predict the future price direction of the market[4]. Jonathan B and Marc L reviews the Fractal Market Hypothesis (FMH) with a focus on financial time series analysis, examining the principles of fractal geometry in conjunction with the Random Walk and Efficient Market Hypotheses[5]. The aim of this study is to demonstrate the

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significant value of fractal features in the field of financial forecasting. To this end, we firstly use fractal features to resample financial time series data with a view to improving the interpretability of the data and the accuracy of the analysis, and empirically test the real data using the Hurst index, and secondly, we use the principle of K-nearest neighbours to construct a prediction model based on the voting rule to validate the validity of the method we used to do the problem.

2 Basic Theory

2.1 Financial Time Series Resampling

In order to validate the self-similarity feature in financial time series, the original financial data will be processed in this study using resampling technique. The purpose of resampling is to convert the time scale of the raw financial time series to other time scale data sets[6]. For example, by resampling the time series at the minute level, it can be converted into financial data at other time scales such as hourly and daily level for our experimental study.

Resample the original data: according to the new timestamp, resample the original data using the following **Equation(1)**:

$$YD\mathrm{s} = Aggregate\,[XDs\,, Group\,(Y\,)] \tag{1}$$

Where X and Y denote the time scale respectively, YDs represents the output of the algorithm, i.e., the dataset under the time scale after the resampling process, XDs is the input, i.e., the historical dataset under the original time scale, Aggregate is the resampling algorithm, and Group denotes the division of the original dataset according to the target time scale (Y).

With the above method, we can transform the original financial time series into datasets with different time scales, which can be used to validate their self-similarity characteristics. This resampling method helps us to understand the characteristics of the financial time series more deeply and provides a basis for subsequent research.

2.2 Fractal market hypothesis(FMH)

FMH argues that the price movements and structure of financial markets are fractal in nature, and that the fractal market hypothesis proposes the existence of self-similar patterns in markets over multiple time scales, with the potential for similar price movements from the short to the long term[7,8].The Hurst index is a key factor in proving the FMH. The significance of the Hurst index is that it can identify whether the time series analysed is stochastic or non-stochastic; after determining that the time series under study is non-stochastic, we can further determine whether it is a persistent or an anti-persistent series; and it is used for evaluating the level of correlation of the time series.

2.3 Voting rule design based on K-nearest neighbour algorithm

In the traditional K-nearest neighbour algorithm, predictions are made based on the closest K data points. However, price fluctuations in financial markets may be influenced by short-term extremes that do not necessarily reflect market trends. To solve this problem, an improved voting rule is introduced, which combines a closing average and a certain time interval of price fluctuations to make a judgement[7].

A time window is first identified to set the range line for the price, and subsequent moving averages of the price are observed relative to the range line. Then compare the range of price activity to the average as a way to assess market movement. If the moving average is consistently above the upper limit of the range, it may indicate an uptrend; if it is below the lower limit of the range, it may be a downtrend; and if the moving average is between the upper and lower range lines, it may be in a state of volatility. The algorithm is as follows **Equation(2):**

$$Label = \begin{cases} 1, P_{BC\_mean} > P_{AC\_80} \\ -1, P_{BC\_mean} < P_{AC\_80} \\ 0, P_{AC\_20} < P_{BC\_mean} < P_{AC\_80} \end{cases} \tag{2}$$

where P_{BC_mean} represents the average of the closing prices in window B, P_{AC_80} and P_{AC_20} represent the 80th and 20th percentile of the closing prices in window A.

By Combining the statistical properties of time series and the analysis of price fluctuation intervals, we design a price trend voting mechanism, as shown in **Figure 1**, which is capable of capturing market dynamics more accurately. Classifying the market trend into three modes, namely up, down and volatile, improves the robustness to market noise, reduces the interference of noise on the trend judgement, and enhances the reliability of the prediction model in practical application.

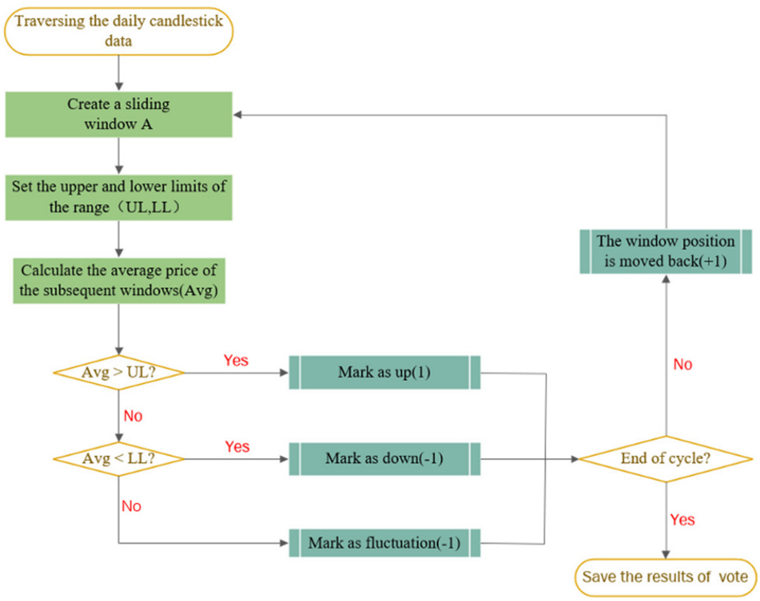

Fig.1. Voting rule algorithm flow design

3 Model Construction and empirical research

3.1 Model Construction

In order to verify the applicability and effectiveness of fractal self-similarity features in the field of financial time series forecasting, historical financial price datasets spanning different time scales are selected for this study. Specifically, the selected data are divided into the to-be-forecast dataset for generating forecasting models and the to-be-searched dataset for constructing corresponding forecasting benchmarks. The study employs a sliding window technique to perform similarity searches between time series windows to identify potential self-similar patterns. Combining the similarity search with the aforementioned voting mechanism, a financial price trend prediction model based on fractal theory is proposed, as shown in **Figure 2.**

Further, based on the voting mechanism defined in the previous sections, the study calculates the confidence level of the prediction model. The voting mechanism is based on the principle of majority voting for a prediction, where the prediction with the highest number of votes is regarded as the output of the prediction, and the proportion of that result among all the votes reflects the confidence level of the model for that prediction. In this way, the actual prediction performance of fractal self-similarity in financial price trend prediction and its reliability are investigated. Where the confidence level is calculated as follows **Equation(3)**:

$$Confidence = \frac{N_{\max}}{N_{all}} \tag{3}$$

where N_{max} represents the number of future price trends with the highest number of votes and N_{all} represents the number of all voting results.

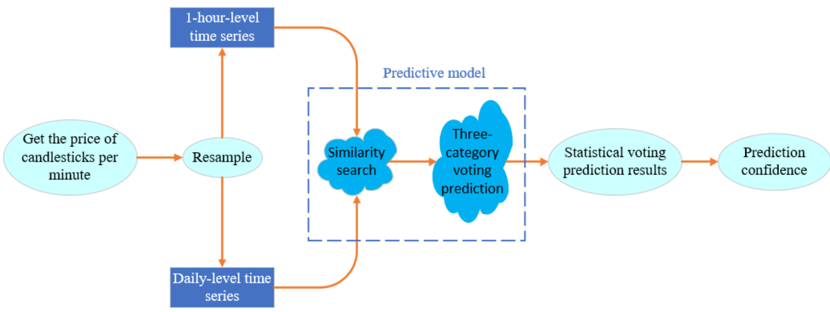

Fig.2. Model run flowchart

3.2 Empirical research

In this study, we use raw foreign exchange K-line price data for EURUSD provided by a trading service provider, spanning the period from January 2001 to November 2022, with data sampling intervals of 1-minute-level(1MDs). Each K-line price data point includes the opening, high, low, and closing prices for each minute, as well as the corresponding date information.

This data is processed using the resampling method in **Section 2.1**.We take one-minute historical data as input to the algorithm, and aggregate the one-minute historical data into hourly and daily historical data through an aggregation algorithm.

The sampling results are shown in the following **Table 1**:

Table 1. Data Abbreviation

Time scale	**Abbr**
1-hour-level Dataset	1HDs
1-day-level Dataset	1DDs

Firstly, in order to verify whether the data used in this study exhibit the fractal self-similarity feature, We use R/S classical analysis to calculate the Husrt index for the above resampled hourly-level and daily-level historical data, knowing that the rescaled polar deviation is R/S, n is the length of the time-increment interval, C is a constant, and the general form of the Hurst index is **Equation(4)**:

$$(R/S)_{\mathrm{n}} = C\mathrm{n}^{H} \tag{4}$$

The Hurst index calculated according to **Equation(4)** is shown in **Table 2:**

Table 2. Hurst exponent calculation results

Time scale	data length	H
Hourly level	134663	0.556
Daily level	6831	0.58

As can be seen from the **Table2**, the Hurst index of the financial time series of the two time scales are 0.556 and 0.58, respectively, according to the meaning of the Hurst index given by the fractal market theory to judge, the value of H is not 1/2, it can be concluded that the financial time series belongs to the non-stochastic series, and the value of H is between 1/2 and 1, which indicates that the time series shows the continuity of the state, Also known as long-term memorability.

To further assess the level of correlation of the data in this experiment, the correlation scale $\rho(\tau)$ grows exponentially between time series increments spaced at intervals of τ, it satisfies a specific relational **Equation(5)**:

$$\rho(\tau) = \tau^{2H-1} - 1 \tag{5}$$

Since the value of H for the two time scales of financial data is between 1/2 and 1, the value of the autocorrelation coefficient between the increments is greater than zero, indicating a positive correlation between them.

Secondly, having confirmed that the financial data we use is consistent with the fractal market doctrine, in order to verify the validity of our proposed model. The resampled hourly-level K-line data (1HDs) and the resampled daily K-line historical data (1DDs) are used as model inputs, and the similarity threshold is adjusted from 0 to observe the change of the triple categorical confidence with the similarity threshold.

Table 3. The confidence level varies with the similarity threshold

Similarity Threshold	Up Number	Total	Confidence
0.4	859	1543	54.52%
0.5	839	1539	55.67%
0.6	855	1493	57.27%
0.7	821	1348	60.90%
0.8	684	1037	65.95%
0.9	237	315	75.24%

4 Conclusion

In this paper, we propose a new financial price trend prediction model based on fractal features to verify the application value of fractal features in financial price trend prediction.Firstly, on the basis of FMH, we confirm the positive effect of FHM on the analysis of the financial market through the validation of the actual financial data.Secondly, in the process of validating our proposed model, we adopt the process of carrying out different time scales to conduct the experimental design method of self-similarity search, and in the study of the given parameters, as shown in **Table 3**, the confidence level of the model prediction increases significantly with the increase of the similarity threshold, which verifies the validity of the proposed method. Therefore, the method proposed in this paper provides new research ideas for fractal features in the study of financial time series, and also proves the important value of fractal features in the field of financial forecasting.

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