FAT: A Fractal-Assisted Technical Trade Method in Stock Markets

Can YANG¹, Jun-jie ZHAI¹ and Xin ZHANG²,*

¹School of Computer Science and Engineering, South China University of Technology, 382 Zhonghuan Road East, Panyu District, Guangzhou, China
²Research Center of Financial Engineering, South China University of Technology, 382 Zhonghuan Road East, Panyu District, Guangzhou, China

*Corresponding author

Keywords: Fractal, Technical indicators, Stock markets, Return.

Abstract. Aiming at improving the accuracy of technical forecast in investment, we proposed a technical trade method assisted by the fractal evolution features of share price, called FAT. This paper first presented a Fractal Quantitative Index (FQI) to control the trade triggered by technical indicators such as Moving Average Convergence/Divergence (MACD), Price Rate of Change (ROC) and Relative Strength Index (RSI). The FQI of a stock is extracted from its price volatility in a certain period of time, and then FAT can make a decision on whether to trade, guided by the state of FQIs of different timescale. With the help of FQI, FAT provided a mechanism to detect and filter out some trading signals that may be noise, in order to control the cost of frequently trading. The experimental results showed that FAT can improve the success probability of trade based on some technical indicators widely used in financial time series. In our conclusion, FAT is a promising technology trading risk control tool worth a deep study.

Introduction

As an important part of financial markets, stock markets have attracted numerous analysts and researchers for decades. To predict stock price is a challenge in reality [1], because it is usually affected by many factors such as political, macro and micro events. Till now, there is still no consensus about the dynamics of the stock market variations. But with the motivation of investors who demand high profit with low risk, a variety of technical indicators are proposed and then widely used in stock market investment [2,3]. However, it is well-known that some technical indicators cannot make a good forecast of the fluctuation of stock price in some markets [4,5]. Some researchers also tried to modify technical indicators themselves [6,7] or just combine them with other technologies, e.g., flag pattern recognition [2], in order to improve prediction accuracy of technical indicators. While the others devote to seek some assistant characteristics of stock market in forecasting. Since Mandelbrot proposed the fractal theory in 1983 [8], the fractal features of financial time series have brought a new way to study the stock markets. Lots of researchers have already found fractal not only exists in stock markets [9,10,11], but also in other aspects, such as earthquake frequencies [12], rate of traffic flow [13] and heart rate [14].

Especially in terms of financial market, lots of researchers have carried out numerical studies. Sun et al [10] indicated that strong correlation exists between the variation of return and the parameters of the multifractal spectra in Hong Kong market and concluded that multi-fractal analysis can be used to predict the variation of stock price with a high precision. In addition, Li et al [9] investigated the fractal dimensions of 30 important stock markets and proposed a model to achieve the considerable profits from the predictable long-term memory. In obvious, to mine the fractal features of stock could be helpful to predict stock price variation and then guide the stock trade for profit. But so far, the previous researchers only utilized fractal features to make predictions, but not focused on combining fractal factors with existing technical indicators, such as MACD, RSI, and ROC.

This paper devotes to using fractal features to improve performance of some technical indicators. We first define a Fractal Quantitative Index (FQI) to control the trade triggered by technical indicators. The formulation of FQI is based on box dimension, a typical fractal dimension. Then, we
propose a Fractal-Assisted Technical trade method, called FAT, in which FQI is used for representing the fractal evolution features of share price in order to guide trade operations of stock markets. Actually, three lines of FQI will be derived from share price in short-term, middle-term and long-term, called FQI-S, FQI-M and FQI-L, respectively. In general, the three FQI lines follows with the evolution of price volatility, and would have formed cross point between them for a period of time, which acts as a motivating checkpoint to drive conventional technical policies after the occurrence of it, in FAT. Finally, we conduct a series of experiments to demonstrate the effectiveness of FAT.

Our main contribution lies in two aspects, one is to define FQI as a fractal index, the other is to propose FAT using the relationship of 3 lines of FQI to guide a technical trade. The remainder of this paper is organized as follows. Section 2 introduces the dataset. And in section 3, we present FAT method in detail. Section 4 shows experimental results for the effectiveness of FAT. Finally, a conclusion and future work are presented in Section 5.

Dataset

We use a dataset downloaded from Yahoo Finance [15], a popular source of data for financial research, and only process and analyze the daily close price of 9 stock indices in this paper. More detailed information is shown in Table 1.

| Stock index | Time period          | Data number | Description                 |
|-------------|----------------------|-------------|-----------------------------|
| DAX         | 1991/07/01-2017/08/18| 6611        | DAX Performance Index       |
| DJIA        | 1985/02/28-2017/08/18| 7558        | Dow Jones Industrial Average|
| CAC40       | 1990/09/11-2017/08/18| 6828        | CAC40                       |
| HSI         | 1994/07/12-2017/08/17| 5700        | Hang Seng Index             |
| KOSPI       | 1993/11/01-2017/08/17| 6111        | KOSPI Composite Index       |
| N225        | 1988/04-2017/08/17   | 7220        | Nikkei 225                  |
| NASDAQ      | 1991/08-2017/08/17   | 8538        | NASDAQ Composite            |
| SP500       | 1985/04-2017/08/18   | 8087        | S&P500 Index                |
| TAIEX       | 1992/03-2017/08/17   | 6211        | TSEC weighted index         |

FAT Method Description

In order to describe our method in detail, we first introduce how to compute FQI with box dimension in fractal theory. And then the framework and procedures of FAT are described in this section. Several used technical indicators and trade policies are given in latter Appendix in the paper.

FQI: Fractal Quantitate Index

In this work, we use box dimension as FQI. In the box-counting method, the space of observation is divided into non-overlapping segments (boxes) of characteristic size \( L \), and the number of boxes \( N(L) \) to cover the data set is counted. As for applying to a time price series, the edge of a box represents time step width, and the space of observation refers to the total length of the series. And if scale invariance exists in the data set, the expression \( N(L) = L^{-D} \) will be held, where \( D \) is the box dimension. From the close price series, one can generate a plot of \( \log(N(L)) \) vs \( \log(L) \) and the exponents \( D \) can be obtained from the slope of a linear regression, as shown in Fig.1, here \( D \) exactly is FQI.

FAT: FQI-Assisted Technical Trade

First of all, we divide each stock index (listed in Table 1) into two parts: training set (first 10 years) and testing set (the rest).

**Step 1: Finding Motivating Checkpoints.** For each stock index, with help of box-counting method we have described above, we can find the motivating checkpoints via FQI. First, calculating
which denotes the FQI in point $t$ of previous $n$ days, then obtain three FQI lines: short-term line ($f_5$), middle-term line ($f_{12}$) and long-term line ($f_{26}$). Further, calculating the $f'_n$ of the three FQI lines by Eq.1.

$$f'_n = \frac{f_n(t) - f_n(t - \Delta t)}{\Delta t} \quad (n = 5, 12, 26).$$

We regard point $t$ as a motivating checkpoint when it is subject to the following condition:

$$\begin{cases} f_{26}(t) > 0 \\ f_{12}(t) > 0 \\ f_5(t - k) < 0 \\ k \in \{0, 1, 2, 3\}. \end{cases}$$

Figure 1. The close price series and box dimension of SSE composite index.

**Step 2: Finding Trade Points.** This step is to find all trade points by the technical indicators (MACD, RSI, ROC), and the specific rules to determine a buy or sell points is described in latter Appendix. Similarly, we also carry out them in both training set and testing set.

**Step 3: Finding the Best Fit Days.** Following step 2, we have obtained $s$ series of trade points, and the goal of this step is to filter out invalid trade points by motivating checkpoints. Here we provide the driven rule that if there is a motivating checkpoint before a trade point found by original method, we regard it as a valid trade point, otherwise filter out it. And the period of $n$ days before the trade point that can be used to detect motivating checkpoint is defined as the best fit days (BFD). Then, we use obtained motivating checkpoints and trade points from training set to find the BFD by setting circulation (1 to $N=30$). Computing corresponding returns and find the BFD with the highest returns, namely $\text{BFD} = \arg\max_{n=1}^{N}(\text{Return}(n))$, here $\text{Return}(n) = \prod_{i=1}^{k_n}(1 + r_i), k_n$ denotes the trade times if $\text{BFD} = n$, and $r_i$ represents the rise of the $i$th time.

**Step 4: Confirming Real Valid Trade Points.** Using the learned BFD from testing set to filter some of invalid trade points, we are able to confirm wanted trade points when happening in test set.

**Step 5: Evaluating Performance.** On the basis of simulation trades with the filtered trade points, we can evaluate the performance of FAT versus original technical trade via calculating corresponding winning rate, average annualized returns and average return of per trade, etc.

**Experiment and Analysis**

In this section, we conduct some experiments to test FAT how to influence the performance of technical indicators in different stock indexes. For sake of simplicity, we set transaction cost rate as 0.3% and regard 246 trade days as a year.

We use several influential stock index series to perform experiments and compare the performance of original technical indicator (MACD, RSI and ROC) with fractal-assisted technical indicator from different aspects, including number of trades(NT), winning rate (WR), average annualized returns (AAR), returns per trade (RPT), etc. The results are showed in Table 2, Table 3 and Table 4. We
found that all the fractal-assisted technical indicators get better performance than the original indicators. It could be caused by the decrease of number of trades, which relatively decrease the number of loss trades and consequently improve accumulated returns.

Table 2. The results of ROC indicator in different stock indices.

| Index | The ROC indicator | The Fractal-Assisted ROC indicator |
|-------|-------------------|-----------------------------------|
|       | NT    | WR    | RPT  | AAR | BFD NT | WR | RPT | AAR |
| CAC40 | 821   | 37.15%| -0.27%| -12.28%| 1 | 138 | 52.90% | 0.13% | 0.46% |
| SP500 | 966   | 33.64%| -0.21%| -8.84% | 1 | 159 | 50.31% | 0.23% | 3.26% |
| DJIA  | 961   | 34.34%| -0.16%| -7.39% | 1 | 166 | 52.41% | 0.82% | 5.98% |
| DAX30 | 758   | 39.71%| -0.16%| -6.56% | 1 | 135 | 55.56% | 0.93% | 4.65% |
| KOSPI | 692   | 38.15%| -0.01%| -4.73% | 4 | 435 | 39.77% | 0.24% | 1.55% |
| HSI   | 641   | 36.04%| -0.16%| -7.62% | 3 | 333 | 40.84% | 0.12% | 0.16% |
| NASDAQ| 761   | 38.24%| -0.19%| -7.70% | 1 | 143 | 52.45% | 0.76% | 5.67% |
| N225  | 864   | 36.57%| -0.26%| -11.96%| 1 | 160 | 46.25% | -0.13%| -1.26% |
| TAIEX | 707   | 39.04%| -0.06%| -3.05% | 1 | 138 | 50.72% | 0.65% | 2.71% |

Table 3. The results of MACD indicator in different stock indices.

| Index | The MACD indicator | The Fractal-Assisted MACD indicator |
|-------|-------------------|-----------------------------------|
|       | NT    | WR    | RPT  | AAR | BFD NT | WR | RPT | AAR |
| CAC40 | 297   | 32.66%| -0.31%| -5.98% | 3 | 139 | 39.57% | -0.18%| -2.53% |
| SP500 | 330   | 36.36%| -0.05%| -1.04% | 1 | 34  | 79.41% | 3.00% | 1.42% |
| DJIA  | 323   | 39.94%| 0.23% | 2.51%  | 3 | 154 | 50.65% | 0.91% | 6.01% |
| DAX30 | 285   | 38.60%| 0.10% | -1.04%| 1 | 43  | 62.79% | 3.50% | 5.76% |
| KOSPI | 233   | 38.20%| 0.15% | -3.06%| 7 | 202 | 42.08% | 0.32% | -0.70% |
| HSI   | 214   | 40.19%| 0.65% | 6.74%  | 4 | 139 | 48.20% | 1.36% | 10.65% |
| NASDAQ| 265   | 42.26%| 0.33% | 3.26%  | 3 | 139 | 50.36% | 1.18% | 6.30% |
| N225  | 273   | 34.80%| 0.01% | -2.77%| 2 | 74  | 45.95% | 0.90% | -0.72% |
| TAIEX | 236   | 39.41%| 0.66% | 5.36%  | 9 | 210 | 42.86% | 0.84% | 5.19% |

Table 4. The results of RSI indicator in different stock indices.

| Index | The RSI indicator | The Fractal-Assisted RSI indicator |
|-------|-------------------|-----------------------------------|
|       | NT    | WR    | RPT  | AAR | BFD NT | WR | RPT | AAR |
| CAC40 | 777   | 36.16%| -0.35%| -12.67%| 2 | 278 | 37.77% | -0.32%| -4.60% |
| SP500 | 892   | 36.10%| -0.27%| -10.20%| 1 | 133 | 60.90% | 0.69% | 2.52% |
| DJIA  | 898   | 35.97%| -0.25%| -9.99% | 1 | 131 | 57.25% | 0.74% | 5.34% |
| DAX30 | 701   | 38.52%| -0.19%| -6.35% | 2 | 248 | 52.02% | 0.38% | 5.64% |
| KOSPI | 638   | 37.30%| -0.24%| -11.41%| 2 | 216 | 40.74% | 0.54% | 4.13% |
| HSI   | 585   | 40.68%| -0.14%| -6.70% | 1 | 101 | 48.51% | 0.77% | 3.64% |
| NASDAQ| 691   | 40.81%| -0.21%| -6.73% | 1 | 112 | 46.63% | 0.74% | 4.66% |
| N225  | 797   | 34.76%| -0.46%| -17.66%| 1 | 117 | 47.86% | 0.04% | 0.74% |
| TAIEX | 650   | 38.93%| -0.35%| -11.84%| 1 | 103 | 45.63% | 1.30% | 5.11% |

Conclusion and Future Work

This paper contributes to a fractal-assisted technical trade method (FAT) using FQI derived from fractal features of share price. The advantage of FAT is to filter out invalid trade signals generated by conventional technical indicators in order to reduce frequently transaction cost. Lots of experiments show that FAT can improve the performance of original technical indicators. Although the profit from FAT is still not enough satisfactory in the paper, FAT may pave a new way to enhance the predictability in stock markets.

In future work, we will further take advantage of these fractal features to find a better trading strategy in stock markets. On the one hand, we continue to research how to make it more accurate
motivating checkpoints in prediction. On the other hand, we will bring neural network or other machine learning technologies into FAT for better performance.

Appendix

Moving Average Convergence / Divergence (MACD)

MACD was proposed by Gerald Apple [16] in 1970s. The MACD indicator has a series of criteria [17] to predict the fluctuation of stock prices. But we only study the relationship between DIF line and DEA line in this paper. The MACD is based on moving averages, which shows the difference between a fast exponential moving average (EMA) and a slow EMA of close prices. If DIF upwards cross DEA line, buy, and if DIF downwards cross DEA, sell. Here P is close price series.

\[
EMA(n)_t = \frac{n-1}{n+1} \times EMA(n)_{t-1} + \frac{2}{n+1} \times P_t ,
\]

\[
DIF_t = EMA(12)_t - EMA(26)_t ,
\]

\[
DEA_t = \frac{8}{10} DEA_{t-1} + \frac{2}{10} DIF_t .
\]

Price Rate of Change (ROC)

ROC was described by Gerald Apple and Fred Hitschler in their book–Stock Market Trading Systems [18]. The ROC indicator provides the slope of the close price chart of a stock with a step size of n days. In this paper, when discussing the ROC indicator, we consider the two lines are ROC line, that is consist of each ROC value, and moving average line (ROCMA) of ROC line. If ROC upwards cross ROCMA, buy, accordingly, if ROC downwards cross ROCMA, sell.

\[
ROC_t = \frac{P_t - P_{t-n}}{P_{t-n}} \quad (n = 12).\]

\[
ROCMAt = \frac{\sum_{i=t-n}^{t} ROC_i}{n} \quad (n = 6).
\]

Relative Strength Index (RSI)

RSI was created by Wilder. J. Welles in his book–New Concepts in Technical Trading Systems [19] in 1978 and can be applied to feature the concept of bull market and bear market ranges [20]. The RSI indicator shows the ratio between averages of close price of rising and falling days. In this paper, we discuss the cross-break between the long RSI line with a period of 12 days (RSI12) and short RSI line with a period of 6 days (RSI6). If RSI6 upwards cross RSI12, buy, and if RSI6 downwards cross RSI12, sell.

\[
nRS_t = \frac{\text{rise}(n)_{avg}}{\text{fall}(n)_{avg}} \quad (n = 6, 12).
\]

\[
nRSI_t = 100 - \frac{100}{1+nRS_t} \quad (n = 6, 12).
\]

where \( \text{rise}(n)_{avg} \) and \( \text{fall}(n)_{avg} \) denote the average of close prices rising and falling days in a period n days before the day t, respectively.

References

[1] S. Barak, J. H. Dahooie, and T. Tichy, “Wrapper anfis-ica method to do stock market timing and feature selection on the basis of Japanese candlestick,” Expert Systems with Applications, 42(2015)9221–9235.
[2] R. Arevalo, J. Garcia, F. Guijarro, and A. Peris, A dynamic trading rule based on filtered flag pattern recognition for stock market price forecasting, Expert Systems with Applications, 81(2017)177–192.

[3] G. S. Atsalakis and K. P. Valavanis, Surveying stock market forecasting techniques–part ii: Soft computing methods, Expert Systems with Applications, 36(2009)5932–5941.

[4] M. Wu and X. Diao, Technical analysis of three stock oscillators testing macd, rsi and kdj rules in sh & sz stock markets, in Computer Science and Network Technology (ICCSNT), 4th International Conference on, 1(2015)320–323.

[5] J. Fang, B. Jacobsen, and Y. Qin, Predictability of the simple technical trading rules: An out-of-sample test, Review of Financial Economics, 23(2014)30–45.

[6] Y. Bai, H. Yin, and S. Liu, Modified kdj index based on wavelet analysis, Electronic Science and Technology, 8(2013) 007.

[7] F. Papailias and D. D. Thomakos, An improved moving average technical trading rule, Physica A: Statistical Mechanics and its Applications, 428(2015)458–469.

[8] B. B. Mandelbrot and R. Pignoni, The fractal geometry of nature, WH freeman, New York, 1983.

[9] D. Li, Y. Nishimura, and M. Men, The long memory and the transaction cost in financial markets, Physica A: Statistical Mechanics and its Applications, 442(2016)312–320.

[10] X. Sun, H. Chen, Z. Wu, and Y. Yuan, Multifractal analysis of hang seng index in hong kong stock market, Physica A: Statistical Mechanics and its Applications, 291(2001)553–562.

[11] H. Xiong and P. Shang, Weighted multifractal analysis of financial time series, Nonlinear Dynamics, 87(2017)2251–2266.

[12] X. Fan and M. Lin, Multiscale multifractal detrended fluctuation analysis of earthquake magnitude series of southern california, Physica A: Statistical Mechanics and its Applications, 479(2017)225–235.

[13] H. Zhang, X. Wang, J. Cao, M. Tang, and Y. Guo, A hybrid short-term traffic flow forecasting model based on time series multifractal characteristics, Applied Intelligence, (2017)1–12.

[14] J. Alvarez-Ramirez, E. Rodriguez, and J. Echeverria, Fractal scaling behavior of heart rate variability in response to meditation techniques, Chaos, Solitons & Fractals, 99(2017)57–62.

[15] Yahoo finance https://www.finance.yahoo.com.

[16] G. Appel, The moving average convergence-divergence trading method: advanced version. Scientific Investment Systems, 1985.

[17] J. J. Murphy, Technical analysis of the financial markets: A comprehensive guide to trading methods and applications. Penguin, 1999.

[18] G. Appel and W. F. Hitschler, Stock market trading systems. Irwin Professional Pub, 1980.

[19] J. W. Wilder, New concepts in technical trading systems. Trend Research, 1978.

[20] C. Brown, Technical Analysis for the trading Professional. McGraw Hill Professional, 1999.