Model 3Gsc

pp. 1-11 (col. fig: NIL)

Physica A xx (xxxx) xxx-xxx

Contents lists available at ScienceDirect

Physica A

journal homepage: www.elsevier.com/locate/physa



# I Trading strategy based on dynamic mode decomposition: Tested in Chinese stock market

# Q2 Ling-xiao Cui, Wen Long\*

Research Center On Fictitious Economy & Data Science, Chinese Academy of Sciences, Beijing, 100190, China School of Economics and Management, University of Chinese Academy of Sciences, Beijing 100190, China Key Laboratory of Big Data Mining and Knowledge Management, Chinese Academy of Sciences, Beijing, 100190, China

# HIGHLIGHTS

- DMD can capture Chinese stock market dynamical patterns well especially in sideways market.
- The spatial information from spatial-temporal coherent structure of DMD modes can improve trading strategy remarkably.
- The SPA tests further prove that DMD can model the behavior of stock market well in a choppy market period with no clear trend.

#### ARTICLE INFO

Article history: Received 15 February 2016 Received in revised form 13 May 2016 Available online xxxx

Keywords:

Dynamic mode decomposition Technical analysis Trading strategy Superior predictive ability

# ABSTRACT

Dynamic mode decomposition (DMD) is an effective method to capture the intrinsic dynamical modes of complex system. In this work, we adopt DMD method to discover the evolutionary patterns in stock market and apply it to Chinese A-share stock market. We design two strategies based on DMD algorithm. The strategy which considers only timing problem can make reliable profits in a choppy market with no prominent trend while fails to beat the benchmark moving-average strategy in bull market. After considering the spatial information from spatial-temporal coherent structure of DMD modes, we improved the trading strategy remarkably. Then the DMD strategies profitability is quantitatively evaluated by performing SPA test to correct the data-snooping effect. The results further prove that DMD algorithm can model the market patterns well in sideways market.

© 2016 Published by Elsevier B.V.

#### 1. Introduction

The efficient market hypothesis was widely accepted in academia, which suggests that current prices of securities have already reflected all the information in current time and one cannot use technical analysis or even fundamental analysis to achieve excess profits. Many early studies used traditional statistical tests to show the invalidation of technical strategy [1, 2]. However in recent decades many scholars began to believe that human psychological and behavioral factors have played an important role in securities price determination [3,4] and the stock price movement can be partially predicted by using the past information. Therefore technical analysis has attracted more and more attention both in practical and theoretical field of finance. Currently most of technical trading strategies try to capture the price trend of the near future and profit from it [5–9]. Although the actual profitability of technical analysis is still controversial [10–15], technical strategies are of growing importance in modern financial investment especially with the advent of automated trading.

Technical analysts usually believe that the past price time series can provide indicators of future price variations. In Refs. [16–18], the profitability of technical trading strategies have been tested in Chinese A-share stock market. Results

http://dx.doi.org/10.1016/j.physa.2016.06.046 0378-4371/© 2016 Published by Elsevier B.V. lts

1

2

3

4

5

6

7

8

9

10

11

12

Please cite this article in press as: L-x. Cui, W. Long, Trading strategy based on dynamic mode decomposition: Tested in Chinese stock market, Physica A (2016), http://dx.doi.org/10.1016/j.physa.2016.06.046

<sup>\*</sup> Corresponding author at: Research Center On Fictitious Economy & Data Science, Chinese Academy of Sciences, Beijing, 100190, China. *E-mail address*: longwen@ucas.ac.cn (W. Long).

### PHYSA: 17239

# ARTICLE IN PRESS

2

L.-x. Cui, W. Long / Physica A xx (xxxx) xxx-xxx

show that Chinese stock market is not efficient in the weak form and some technical trading strategies can offer significant 1 2 profitability. The profitability of technical strategies can be understood that they detect patterns or features of a less efficient market. In this work, we adopt the dynamic mode decomposition (DMD) [19–22] method to capture the intrinsic dynamics in 3 stock market and apply it to Chinese A-share stock market to test its profitability. Unlike most of the model-driven methods 4 which need to impose assumptions, the DMD is a data-driven method that any postulations about the underlying dynamical 5 information is not needed. Compared with traditional time series analysis method, the most novel feature of DMD is that 6 it combines features of the power spectral analysis in temporal component and the principal components analysis (PCA) in spatial component simultaneously. The DMD method has been originally used in the field of fluid dynamics for experimental 8 or simulative data mining. In fluid mechanics, fluid flows are infinite-dimensional nonlinear systems. The DMD method q produces a least-square regression to reduce the high-dimensional system to a lower linear dynamical system in the form 10 of DMD modes and corresponding eigenvalues. The DMD modes are coherent spatial structure of the fluid flows and the 11 eigenvalues show the systems' evolving behavior. Note that in fluid dynamics community there are other technics to extract 12 coherent structures. For example, the proper orthogonal decomposition (POD) modes [23], global eigenmodes, frequential 13 modes [24]. Both POD and DMD are snapshot-based post-processing algorithms. POD modes are spatial orthogonal with 14 multi-frequential temporal component while DMD modes are non-orthogonal but each of them possesses a single temporal 15 frequency. This non-orthogonal property of DMD is essential when capturing important dynamical effects in systems with 16 non-normal dynamical generators [25]. Recently many improved DMD algorithm have also been proposed. The multi-17 resolution DMD has been introduced in Ref. [26] and a sparsity-promoting variant of the standard DMD can be found in 18 Ref. [27]. 19

Many research have showed that some dynamical behaviors of economic systems resemble the features of complex 20 systems, such as multi-scale phenomenon, power-law distribution and critical behavior [28–31]. The basic assumption in 21 this paper is that the stock market is a complex dynamical system. In stock market, stock prices are interactive and can 22 be regarded as the measurements of such complex systems. As an equation-free technique, DMD method allows one to 23 focus his attention exclusively on historical data to discover the dynamical properties of financial system. More specifically, 24 the time series of stocks' price data provide the series of snapshots of DMD. By extracting the dynamical pattern, one can 25 make prediction about the near future states. In Ref. [32], DMD algorithm has been used to develop trading strategies in US 26 stock market. By extracting key temporal coherent structures, DMD trading scheme can inform buy/sell/hold investment 27 decisions. The results in different sectors show that DMD trading strategies can easily beat the benchmark. In this work, we 28 will further show that the spatial-temporal coherent structures in DMD modes can be used to make not only market timing 29 strategies but also portfolio selection strategies. Our results show that the strategy with only timing decision part can barely 30 beat some simple technical strategy, while the strategy with both timing and portfolio selection parts will be improved 31 significantly. The most noticeable aspect for implementation of DMD in finance is that financial market is an open complex 32 adaptive system, unlike the fluid flows or other physical systems, the dynamical patterns in financial market are changing all 33 the time. This leads to the difficulty of deciding the time scales in DMD. In this work, we use the same learning algorithm as 34 showed in Ref. [32] to dynamically choose the best time scales. Also the original DMD cannot model the exogenous influences 35 on stock market. One can take into account other exogenous variable by adopting the DMD algorithm with external signal 36 which can be found in Ref. [33]. In this work, we adopt the Superior Predictive Ability (SPA) test [34] to quantitatively 37 evaluate the DMD algorithm's predictive ability in Chinese A-share stock market. The SPA test was proposed to eliminate 38 the data-snooping effects which occurs when the same historical data is used more than once for model selection. There is 39 high possibility that the best fitted model is chosen by luck rather than its actual forecasting ability. 40

The paper is arranged as follow: In Section 2, we briefly introduce the DMD method. In Section 3, we design two trading strategies based on DMD and back test it in Chinese A-share stock market. In Section 4, we adopt the SPA test to quantitatively evaluate the forecasting ability of these two strategies. The conclusion and the discussion of future improvement can be found in Section 5.

### 45 **2.** Dynamic mode decomposition method

53

56

The dynamic mode decomposition is a data processing algorithm that extracts spatial-temporal coherent structures in a given complex system. It is an equation-free, data-driven method that can capture important dynamical effects even without knowing fully, or partially, the underlying governing equations. DMD has been wildly used in the fluid dynamics communities and atmospheric science. Here we briefly outline the key structures of DMD.

<sup>50</sup> Consider *n* data or measurements collected at time  $t_i$  from a given nonlinear system, assume that the data are equispaced <sup>51</sup> in time, with a time step  $\Delta t$  and the collection time starts from  $t_1$  to  $t_m$ . These *m* snapshots can be arranged into an  $n \times m$ <sup>52</sup> matrix.

$$\boldsymbol{X} = \begin{bmatrix} \boldsymbol{x}_1, \boldsymbol{x}_2, \boldsymbol{x}_3, \dots, \boldsymbol{x}_m \end{bmatrix}$$
(1)

where the vector  $\mathbf{x}_i$  is the data collected at time  $t_i$ . The purpose of DMD is to extract important dynamical information from matrix  $\mathbf{X}$ . We can define two matrices from  $\mathbf{X}$  as follow:

$$X_1 = \begin{bmatrix} x_1, x_2, x_3, \dots, x_{m-1} \end{bmatrix}$$
(2)

Please cite this article in press as: L.-x. Cui, W. Long, Trading strategy based on dynamic mode decomposition: Tested in Chinese stock market, Physica A (2016), http://dx.doi.org/10.1016/j.physa.2016.06.046

Download English Version:

https://daneshyari.com/en/article/7377051

Download Persian Version:

https://daneshyari.com/article/7377051

Daneshyari.com