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Trend following algorithms in automated derivatives market trading

Simon Fong *, Yain-Whar Si, Jackie Tai

Department of Computer and Information Science, University of Macau, Macau

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ABSTRACT

Trend following (TF) is trading philosophy by which buying/selling decisions are made solely according to the observed market trend. For many years, many manifestations of TF such as a software program called Turtle Trader, for example, emerged in the industry. Surprisingly little has been studied in academic research about its algorithms and applications. Unlike financial forecasting, TF does not predict any market movement; instead it identifies a trend at early time of the day, and trades automatically afterwards by a pre-defined strategy regardless of the moving market directions during run time. Trend following trading has been popular among speculators. However it remains as a trading method where human judgment is applied in setting the rules (aka the strategy) manually. Subsequently the TF strategy is executed in pure objective operational manner. Finding the correct strategy at the beginning is crucial in TF. This usually involves human intervention in first identifying a trend, and configuring when to place an order and close it out, when certain conditions are met. In this paper, we evaluated and compared a collection of TF algorithms that can be programmed in a computer system for automated trading. In particular, a new version of TF called trend recalling model is presented. It works by partially matching the current market trend with one of the proven successful patterns from the past. Our experiments based on real stock market data show that this method has an edge over the other trend following methods in profitability. The results show that TF however is still limited by market fluctuation (volatility), and the ability to identify trend signal.

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1. Introduction

Trend following (TF) (Fong & Tai, 2009) is a reactive trading method in response to the real-time market situation; it does neither price forecasting nor predicting any market movement. Once a trend is identified, it activates the trading rules and adheres rigidly to the rules until the next prominent trend is identified. Trend following does not guarantee profit every time, but nonetheless in a long term period it may probably profit by obtaining more gains than loses. The nature of TF makes it as an ideal ingredient in implementing a decision-making component in automated trading software where human intervention is not required in automatic buying and selling. Automated trading here is referred to an 'auto-pilot' mode by which the software system decides when to buy or sell a stock (in a form of option, future contract, warrant, etc.) from the derivative market. Though the philosophy of trend following is simple – identify a current market trend and trade strictly according to the pre-defined rules (sometimes known as strategies), how the rules or strategies should be formulated has become an important research problem that deserves attention from researchers. Rules such as when to buy and sell or when to open and close a position, as signaled from the market trend have a direct impact into the profitability of automated market trading. TF algorithms in this context are termed as automated trading methods that are guided by the current market trend (signals from the trend) and specified by the rules (reactions to the trend). For an example of a most basic TF algorithm, buying and selling are cued by the conditions when the market trend which is represented by its moving average rises over an up-threshold, and falls below a down-threshold respectively. The values of the thresholds are predefined as a part of the trading rules.

To the best of the authors' knowledge, surprisingly, TF algorithms have not been investigated in the computer science community. In contrast a lot of research papers on stock market forecast and prediction by soft computing can be found in literature. Fig. 1 classifies clearly that trading algorithms can be powered by two different domains of techniques, namely Predictive and Reactive. Predictive types of forecasting and trading in a stock market have a long history in academic research, which generally covers non-linear prediction by artificial neural works, decision trees and other regression models. These tools usually aim at predicting the future market movement ahead by analyzing over the historical data. TF algorithms however, belong to the latter category, which conduct trading decision solely by reacting to the current market trend. There are several variants of TF algorithms, depending on how the rules and the predefined thresholds are

* Corresponding author. Tel.: +853 83974460; fax: +853 2883 8314.
E-mail address: ccfong@umac.mo (S. Fong).

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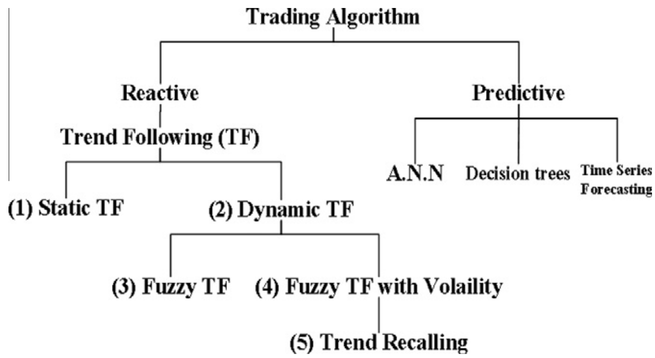

Fig. 1. Classification of trading algorithms.

specified. Without the need of training up a decision model, and subsequently updating it, like those under the predictive type, TF is readily implemented as a rule-based system in automated trading software.

The objective of this paper is to present a performance comparison of the five TF algorithms which have been recently proposed by the authors. The contribution of this paper is twofold: Theoretically insights are gained in terms of performance strength, weakness and characteristics of each TF algorithm under test, so that prospect of future research in improving from the existing TF algorithms is warranted. Secondly the TF algorithms presented in this paper serve as useful designs of the decision-making core for implementing an automated stock market trading system. The structure of this paper is as follow: Section 2 describes four possible implementations of TF algorithms, highlighting especially their shortcomings and possible improvement. Section 3 presents in details the latest addition to the family of TF algorithms called trend recalling algorithm. A simulation prototype of automated trading system is developed, for the purpose of evaluating their performances comparatively. The experiments carried out by the simulator are reported in Section 4. Section 5 concludes.

2. Trend following algorithms

In this paper, we discuss on the design of an automated trading system, which incorporates these trend following algorithms, which is a core element of the system, and the application of this type of system in financial market. We also investigate how the market fluctuation can affect the overall performance, and bring new perspective to handling the financial cycles.

One of our goals is to build up this automated trading system, which primarily operates on financial derivative market (Mayo, 2003), such as the Hang Sang Index Futures Contract that trade on HKFE (Hong Kong Future Exchange) or the Dow Jones Industrial Average Index Futures Contract that trade on CBOT (Chicago Board of Trade). In this thesis "Hang Sang Index Futures" is selected as the primary simulation market, although the system can be applied on any market theoretically.

By using only historical market data, the system is able to react according to real-time market state, and make trade decision on its own. To reduce the overnight risk and cost-of-carry, trade will be performed on a daily basic only, which means no contracts will be carried overnight. The P&L (profit and loss) on each trade will be recorded and accumulated as the total of ROI (return on investment), which is a common indication for the performance of an investment in financial world.

2.1. Static TF algorithm

The basic practice of trend following is to find the trend, identify trade signals and trade along with them. Based on a phenomenon pointed out by Murphy (1999), which says "A trend in motion is more likely to continue than to reverse", TF algorithm can possibly reap benefit by recognizing the direction of the trend at the start and bet on that direction for the remaining length of the trend, as long as the trend does not reverse. For confirming whether a trend is now in effect of development, it is necessary to measure how much it has progressed since the last reverse, and then ensure the current progress is greater than the minimum threshold that it has risen or fallen. This is to test by comparing the trend momentum to a specific level. If the amount of increase or decrease of a trend has already exceeded a certain level, a significant trend is assumed to emerge and trade signals can be safely generated accordingly. These marks or minimum levels will have to be chosen carefully in order to avoid false signals as a result of temporary fluctuation or short-term velocity of the trend. If they are too long, few positions will be opened or closed because it is not often that a large scale charge on a trend would occur. If the marks are chosen too short, the trading is prone to be buying very frequently and selling too early, leaving little or no profit in between the trades.

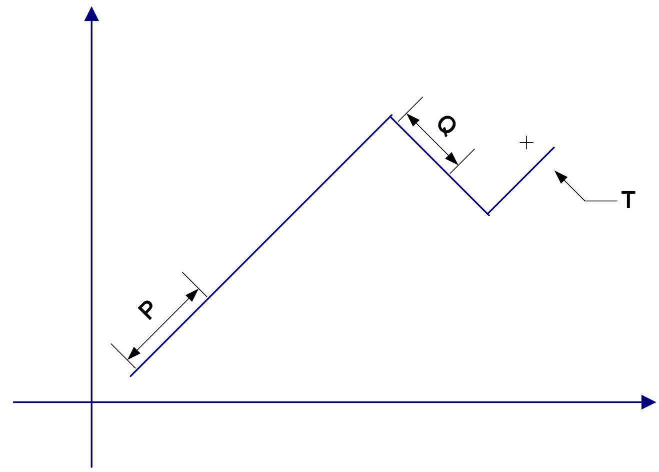

Fig. 2. Illustration of P and Q applied on trend T.

In this Static TF algorithm, two constants are used to function as the two comparison marks, only over which a substantial change in the trend would trigger the trading system to open or close a position accordingly. These constants are defined as P and Q, where P is the amount of up-trend required for opening a position, and Q is the amount of opposite trend required to close this position.

Fig. 2 illustrates the basic concept of TF. T denotes as the market price trend. For example on the diagram, it will open a long position when the trend T advances over P, and will close out this position when the trend T declines for more than Q.

In reality market price does not move in a straight line. It is therefore impractical to apply the P and Q rules directly on the trend T, because the frequent fluctuation will alarm off too many signals of trading actions. An Exponential Moving Average (EMA) algorithm is used to smooth out this fluctuation, which equation is shown as follow:

$$EMA_{(t)} = \left(price_{(t)} - EMA_{(t-1)} \times \frac{2}{n+1}\right) + EMA_{(t-1)} \qquad (1)$$

Fig. 3 demonstrates the effect of the smoothing.

This trading algorithm is represented by the following pseudocode (Algorithm 1), in which P and Q are static constants. Their values are obtained by studying the historical data and deriving the optimal combination of P and Q. Different combinations of P and Q are tried by brute-force, testing out for the best values that generate the maximum profit in the simulation. $EMA(T)$ is the

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