Integrating a Piecewise Linear Representation Method with Dynamic Time warping system for Stock Trading Decision Making

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Abstract

Stock turning points detection is a very interesting subject arising in numerous financial and economic planning problems. In this paper, a piecewise linear representation method with Dynamics Time Warping system for stock turning points detection is presented. The piecewise linear representation method is able to generate numerous stocks turning points from the historic data base, then the Dynamic Time Warping system will be applied to retrieve similar stock price patterns from historic data for training the system. These turning points represent short-term trading signals for selling or buying stocks from the market. A Back-Propagation neural network (B.P.N) is further applied to learn the connection weights from these historic turning points and afterwards it is applied to forecast the future turning points from the set of test data. Experimental results demonstrate that the system integrating PLR and neural networks can make a significant amount of profit when compared with other approaches using stock data.
Key words: Stock turning points, Dynamics Time Warping system, PLR method, Back-Propagation neural network

1. Introduction

The stock turning point is a local peak or valley during a stock price variation. The turning point is also represented as a short-term trading signal. If an investor tries to sell or buy stocks during these turning points, he can make a certain amount of profit as long as the price difference between the peak and valley is greater than the transactional cost. However, these turning points are very difficult to be detected or even observed since the price variation is subject to high dimensionality and non-stationary

This research takes a different approach by using the piecewise linear representation method with neural networks to predict the future turning points of a stock price. Turning points represent a close relationship among stock closed price and various technical indexes and these data points will be studied intensively through a neural network. The local stock turning points can be detected using PLR preprocessing technique. Later on, these turning points governing the relationship among stock closed price with various technical indexes will be inputted into the neural network (BPN) for training and the trained neural network model can be applied as a predicator for predicting the future turning points in the set of test data. Dynamic time warping system is further applied to retrieve similar stock price pattern from historic data to train the system effectively. Finally, an investor then can apply these future turning points as trading signals and make significant amount of profits.

2. Literature Survey

The stock market is a complex system where process of decision-making involves difficulties, since numerous factors and a high level of noisiness influence the stock price variations. Technical analysis (TA) is one of the most popular methods widely used by stock traders [4]. Traditionally, TA proposes a set of investment rules to the investor. However, the use of individual trading rules is not quite effective from the investor's point of view [5]. Since application of numerous rules is complicated and the combination of trading rules is hard to find, the overall results are not that satisfactory.

The recent new approaches based on evolutionary computations and artificial neural networks (ANN), have gained wide popularity in problems whose solution space is so complex and large that it is impossible to use the traditional optimization methods. The application of ANN in stock market prediction has its advantages and disadvantages. For example,[7][8] showed that ANN could be successfully used in short-term series prediction. The application of ANN is especially effective when the link between the influencing and the dependent variables is nonlinear and very noisy, which is typical of a stock market. The main drawback in the ANN application is that they do not provide any insight of the underlying process and prevent us from obtaining a specific collection of rules, therefore decision-making relying solely on ANN functioning is not applicable. On the other hand, the application of genetic programming (GP)

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eliminates those problems and allows creating more complex rules out of simple ones, but it requires great computational effort. Therefore, it is suggested that the use of hybrid systems can help to avoid the weaknesses while integrating their individual strengths. Related techniques applied in this research are briefly introduced and surveyed in the following.

2.1 Technical Analysis

TA is the process by analyzing the historical stock prices to determine the possible future trends of a stock price movement. TA can explore the inner information of the market and assume that all the necessary factors refer to the stock exchange information as a result of price dynamics research. Thus, technical analysts affirm that the research of the past share exchange rate and the transaction amount combination allows the investigator to determine the exact moment when the shares are either overvalued or undervalued. To determine these time points, analysts form a group of technical rules (TR) based on technical indicators (TI). The aim of each rule is to generate at the right time either the buy signal when a bull market is expected or sell signal when a bear market is arriving. The better the rules, the higher the earnings are. Every TI is a function of time-series values whereas, one TR is a function of the values of TI and more independent parameters. The output of a TR function can be either buy, hold or sell signals. Some more detailed information on TA could be found in [1].

2.2 Dynamic Time Warping

Dynamic Time Warping system was developed by [6] and it is a pattern matching method for time series data analysis. The key idea of Dynamic Time Warping (DTW) is that any point of a series can be (forward and/or backward) aligned with multiple points of the other series that lie in different temporal, so as to compensate for temporal shifts.

The Dynamic Time warping has been used in areas such as time-series forecasting and Data-pattern recognize, including [9]. This research tries to improve the pattern learning effect by retrieving historic data through dynamic time warping, and the forecasting accuracy of the model can be further enhanced by this effective learning.

2.3 Artificial Neural Networks

The neural network is first established through a training phase, whereby example inputs are presented and the network is trained to extract relevant information from these patterns. Subsequently the network has the capability to generalize, so that an input pattern not yet seen may also be processed. The range of tasks that the neural network can be applied to vastly exceeds any traditional technique. ANN, in particular, has gained a great popularity in forecasting tasks, where the link between the influencing factors and the values being predicted is nonlinear and noisy. Additional information about ANN functioning principles as well as ANN application in financial area could be found in [2].

Prediction of a financial market is rather challenging due to chaos and uncertainty of the system. This study makes two attempts to forecast the turning points of a stock movement: 1. A PLR approach is applied to generate possible historical turning points from historical stock price data for neural networks training and learning applications. 2. A modified neural network with Dynamics Time-wrapping technique is developed to train the system and to predict the future turning points of a stock price movement.

3.Applying DTW-PLR to Generate Historical Turning Points

This research applies a Piecewise Linear Representation technique to effectively select turning points from the historic stock price database. However, the historic data base is retrieved by using Dynamic Time warping to filter similar data patterns. The flow chart of the DTW-PLR model is described as follow: (Please see figure 1)

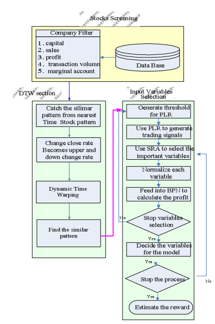

Fig 1 The flow chart of the DTW-PLR model

3.1 Dynamics time warping

The Definition of Dynamics time warping is based on the notion of warping path. Let d be the $n * n$ matrix of pair wise squared distances between samples of R and $S, d[i,j]=(R_i-S_j)^2$. A warping path $W=\langle w_1,w_2,.....,w_k\rangle$ is a sequence of $K\ (n \le K \le 2n-1)$ matrix cells, $w_k=[i_k,j_k]\,(1\le i_k,j_k\le n)$,such that the following conditions hold: Boundary conditions: $w_1=[1,1]$ and $w_k=[n,n]$ i.e., W starts in the lower-left cell and ends in the upper-right cell;

Continuity: given $w_{k-1}=[i_{k-1},j_{k-1}]$ and $w_k=[i_k,j_k]$ then $i_k-i_{k-1}\le 1$ and $j_k-j_{k-1}\le 1$. This ensures that the cells of the warping path are adjacent; Monotonicity: given $w_{k-1}=[i_{k-1},j_{k-1}]$ and $w_k=[i_k,j_k]$, then $i_k-i_{k-1}\ge 0$ and $j_k-j_{k-1}\ge 0$, with at least one strict inequality. This forces W to progress over time.

Any warping path *W* defines an alignment between *R* and *S* and, consequently, a cost to align the two series.The (squared) *DTW* distance is the minimum of such costs, i.e., the cost of the optimal warping path, W_{OPT} :

$$DTW\left(R_1^n,S_1^n\right)^2=\min_{W}\left\{\sum_{[i_k,j_k]\in W} d[i_k,j_k]\right\}=\sum_{[i_k,j_k]\in W_{OPT}} d[i_k,j_k] \qquad (1)$$

The *DTW* distance can be recursively computed using an O(n2) dynamic programming approach that fills the cells of a *cumulative distance matrix D* using the following recurrence relation as shown in Fig. 2.

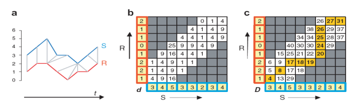

Fig 2 Computing the DTW distance with a Sakoe – Chiba band of width b = 2: (a) optimal alignments; (b) the d matrix of pair-wise sample distances; (c) the D cumulative distance matrix; highlighted cells constitute the optimal warping path W_{OPT}.

$$D[i,j]=d[i,j]+\min\{D[i-1,j-1],D[i-1,j],D[i,j-1]\}\ (1\le i,j\le n) \qquad (2)$$

and then setting $DTW\left(R_1^n,S_1^j\right)=\sqrt{D[n,n]}$.

Note that $\sqrt{D[i,j]}=DTW\left(R_1^i,S_1^j\right),\forall i,j,$ since the DTW distance is well-defined even when the two series have different lengths [6].

In practical applications, warping paths are commonly subject to some global constraints, in order to prevent pathological alignments. The most commonly used of such constraints is the Sakoe – Chiba [11]of width b, that forces warping paths to deviate no more than b steps from the matrix diagonal (see Fig. 2(b)). It is worth noting that, besides reducing the complexity of computing DTW to O(nb), rather surprisingly a band of limited width b leads to better results in classification tasks, even when b is a small fraction (say, 3-4%) of n [3].

In this research, DTW is applied to retrieve the similar data pattern from historic stock price data. The forecasting period from financial stock time-series data will be identified and stored as a template for studying. For example, a six-day stock price data with the stock closed price at 42.8. Then, these succeeding data, i.e., (43.5, 43.2, 44.3, 43.9, 44.8) within the template, will be converted into the price variations within each date instead of the stock price, i.e., (+0.7, -0.3, +1.1, -0.4, +0.9). Dynamic Time Warping is then applied to find the similar pattern of (+0.7, -0.3, +1.1, -0.4, +0.9) within the historic data.

3.2 Piecewise Linear Representation, PLR

As the historic data is retrieved using DTW, the next step will be to identify the trading points of stocks as observed from the variation of technical indexes. However, these turning points are not so easy to observe for every investor. Therefore, this study attempts to develop an intelligent trading point prediction system. Investors can make a good trading strategy by applying this intelligent model.

The main procedures of PLR in identifying the turning point are described as follows:

3.3 Divided the raw data into sub-segments

PLR can be applied as a sliding window to find the turning points of a financial time series data. This method needs to setup the size of the sliding window, and to find the relative maximum or minimum points of the data within the time window as the turning points. However, this may not be a very good approach; since the turning points depend upon what the sliding window size is. If the window size is not properly decided, the sub-segments generated by PLR may lead to the wrong decision for the future trading points. Therefore, the profitability of the method is questionable. Instead, this research takes all selected historical data for piecewise representation. Then, the turning points decided will be more representative and can be applied for prediction of the future trading points. Another key factor to be decided is the threshold value of a piecewise representation and it will be explained in the following.

3.3.1 Setup the threshold value (δ) of PLR

Larger threshold value will create long trend patterns; on the contrary, the patterns are very sensitive when the threshold value is very small. This research adopts genetic algorithms as a fine-tune operator for this key factor – threshold value (δ). Depending on the variation of each stock in the historical data, the threshold value is setup within the range of [0.01, 5.0] accordingly.

3.3.2 Trading point decision

PLR is developed for pattern matching; it cannot automatically generate trading points of a stock for investors. The contribution of this research is to convert outputs from PLR to generate possible trading points.

In addition, the algorithm of trading point's generation by PLR is represented using virtual codes as listed in Figure

2.The quality of the trading points generated by PLR is determined by the threshold value (δ). In tradition, the judgment of a trading signal is decided by financial experts' opinions. If the trading signal is not judged properly, the investor can make a mistake and lose money. However, these opinions can be directly linked to the decision of the threshold value (δ). Therefore, this study applies DOE to optimize the threshold value of PLR instead and with the expectation to generate better sub-segments and to make more profits.

```
Procedure BuildTree (S).
Input: segment S.
Let S be represented as x[1..n], y[1..n].
   If (Max (y[1..n] == y[1] OR Max (y[1..n] == y[n])
   OR Min (y[1..n] == y[1] OR Min (y[1..n] == y[n]))
      Create a node in the hierarchy for this segment;
      Draw a line between (x[1],y[1]) and (x(n), y(n));
      Max d = maximum distance of (x[i],y[i]) to the line;
      If (Max d < threshold ( δ ))
         This segment is good enough; no further work
      Else
         Let (x[j], y[j]) be the point with maximum distance to the line.
         Break the segment S into S1 and S2 at the point (x[j],y[j]);
         PARENT (S1) = S;
         PARENT (S2) = S;
         BuildTree (S1);
         BuildTree (S2);
      End If
   Else
      Break the segment at the maximum and/or minimum point(s) into smaller ones S1,..., Sm;
      For i = 1 to m
         PARENT (Si) = PARENT (S);
      End For
      Delete (S);
      For i = 1 to m
         BuildTree (Si)
      End For
End If
```

Fig. 2 The virtual code of the PLR

3.4 A Back Propagation Network, BPN

After generate the sub-segments by using PLR, the trading signals need to be transformed before fed into BPN. By adopting PLR, the sub-segments will be divided and the trends of time series data are defined as follows:

$$\begin{aligned} &If \quad E_{k.}x \geq E_{.}x + \delta \quad , \quad Etrend = UP \\ &If \quad E_{k.}x \leq E_{.}x - \delta \quad , \quad Etrend = DOWN \\ &If \quad E_{.}x - < E_{k.}x < E_{.}x + \delta \quad , \quad Etrend = NOTREND \end{aligned} \tag{3}$$

Where, $E_{k.}x$ means the stock price of the k-th turning points; and $E_{.}x$ is the stock price of the current turning points. The trend will be transformed as an output value of BPN and they are listed in Table I.

TABLE 1 The illustration of trading signals transformation

Time series	Stock price	Turning point	Trend	Trading point	Trading signal
1	46.2	•	Up	Buy	0
2	49.1				0
3	48.2	•	Up	Buy	0
4	54.3				0
5	56.6	•	Down	Sell	1
6	53.5				1
7	54.6				1
8	50.2				1
9	48.8	•	Up	Buy	0
10	51.5	•		Sell	1

We find that the trading signals transformation need to be related to the vibration of stock price. Therefore, the trading signals are further defined as follows:

If up-trend

$$t_i = \left[\frac{C_i - \min\{C_i, C_{i+1}, C_{i+2}\}}{\max\{C_i, C_{i+1}, C_{i+2}\} - \min\{C_i, C_{i+1}, C_{i+2}\}} \right] \cdot 0.5 \tag{2}$$

If down-trend

$$t_i = \left(\left[\frac{C_i - \min\{C_i, C_{i+1}, C_{i+2}\}}{\max\{C_i, C_{i+1}, C_{i+2}\} - \min\{C_i, C_{i+1}, C_{i+2}\}} \right] \cdot 0.5 \right) + 0.5 \tag{3}$$

where C_i means the stock price of the i-th transaction day. This transformation will be more appropriate for representing the momentum of a stock price. The illustration of this process is shown in Figure 3.

All t_i values will be fed into BPN for training the network to learn the best connection weights. After the training process, the outputs of BPN ([0.0, 1.0]) need to be transformed into trading decision in the testing period. In this study, the average of t_i in training stage will be regarded as the boundary when make a trading decision as shown in Table II and Table III. In the case example, 0.508 is the boundary.

4. Numerical Examples

In this section, three different stocks are selected for performance comparisons of the system. One is the up-trend (AU Optronics Corp. (AUO), one is the down-trend (D-Link Corp. (D-LINK), and other is steady (UMC Corp. (UMC)). and the overall comparison of all instances will be presented in the last figures.

TABLE 2 Transformation of t_i

Time series	Stock price	Trading signal	t_i
1	46.2	0	0
2	49.1	0	0.07[illegible]77
3	48.2	0	0
4	54.3	0	0.129032
5	56.6	1	1
6	53.5	1	0.8[illegible]5
7	54.6	1	1
8	50.2	1	0.759259
9	48.8	0	-
10	51.5	1	-

TABLE 3 The final trading decision from BPN

Time series	Stock price	Out from BPN	Trading decision
1	81.8	0.647	Buy
2	82.9	0.408	Sell
3	82.3	0.616	Buy
4	85.5	0.436	
5	88.4	0.486	Sell
6	87.5	0.558	
7	86.3	0.691	
8	87.6	0.676	Buy
9	89.3	0.507	
10	90.6	0.501	Sell

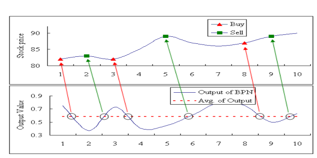

Fig 3 The correlation between trading signals and output values from BPN

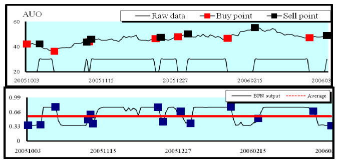

Fig 5 The Forecasted Trading points by BPN in AUO(Up -trend decision)

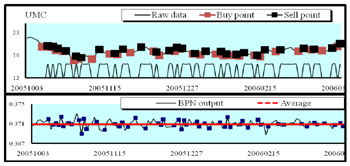

Fig 6 The Forecasted Trading points by BPN in UMC Corp(Steady-Trend decision)

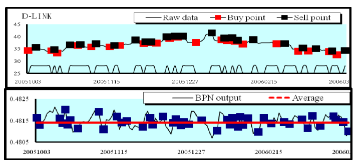

Fig 7 The Forecasted Trading points by BPN in D-Link Corp.(Down-Trend decision)

This section will analyze the experiments, based on the measurer (rate of return), all the results of these nine stocks are shown in Table .

Table IV
The overall comparisons of BPN, PLR, and IPLR in Rate of return

Stocks	BPN	PLR	DWT+PLR
AUO	90%	47%	95%
UMC	78%	74%	98%
D-LINK	51%	50%	85%

5. Conclusion

A considerable amount of research has been conducted to study the behavior of a stock price movement. However, the investor is more interesting in making profit by providing simple trading decision such as Buy/Hold/Sell from the system rather than predicting the stock price itself. Therefore, we take a different approach by applying PLR to decompose the historical data into different segments. As a result, turning points (trough or peak) of the historical stock data can be detected and then be input into the Back propagation Neural Network to train the connection weight of the model. Then, a new set of input data can trigger the model when a buy or sell point is detected by the BPN. An intelligent piecewise linear representation model is further developed by integrating the Genetic Algorithm with the PLR to evolutionarily improve the threshold value of PLR to further increase the profitability of the model.

The proposed system is tested on three different types of stocks, i.e., up-trend, steady and down-trend. The experimental results show that the IPLR approach can make significant amount of profit especially on up-trend, down-trend then steady. In summary, the proposed system is very effective and encouraging in predicting the future trading points of a specific stock. However, there is one issue to be further discussed and that is the price variation of the stock. It is observed that if the price variation of the current stock to be forecasted either in a up-trend or a down-trend then it is better that we trained our BPN with the similar pattern, i.e., either in a similar up-trend or down-trend period.

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